Multiscale modelling for optimal process operating windows in Friction Stir Welding

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Dedication

To Silvia, my mom, and my brother Cesar and little sister Lesli

for all their love, unconditional support, encouragement and patience.

And with special love, to my grandma,

the inspiration of our lives.

Abis your pure soul has enlightened every day of my live,

words cannot describe the immense love and admiration

that I have for you and I cannot thank you enough

for all your love and blessings,

this is for you, my sweet and beautiful grandma.

Abstract

The modelling, prediction and performance monitoring of manufacturing processes are key research aspects for the optimal design and quality control, in particular for complex thermomechanical processes. Numerical-based modelling techniques such as Finite Element and Computational Fluid Dynamics are widely and used approaches to successfully model complex thermomechanical industrial processes. For real-time applications, however, such modelling techniques are not suitable due to the significant computational cost. In addition, the lack of in-depth understanding of some complex processes, such as Friction Stir Welding (FSW), prohibits the creation of accurate physics-based models. Data-driven modelling offers an alternative solution to model-based analysis of complex processes via the creation of computational structures that are capable of 'learning' from process data.

In this thesis, a new data-driven modelling framework is proposed, focusing on real-time processing capability of a complex (and ill-understood for some materials) thermomechanical process: FSW. Specific challenges that this research work addresses includes availability of low number of process samples/data, modelling in multiple process scales (micro-, meso-, macro-), real-time processing capability (hence low computational cost), creation of new monitoring techniques capable of automatically identifying abnormal behaviour (novelty detection) and process optimisation which acts in real-time to ensure optimal Process Operating Windows (POW) in multiple scales. A special research focus of the presented research work is human-centric systems in manufacturing, hence the aspects of natural language feedback to the user and simple (transparent to the non-expert) yet accurate models are also investigated.

The proposed hybrid model-based framework is based on Soft Computing, due to the need for system transparency and computational simplicity. This includes Fuzzy Logic-based approaches as well as Neural-Fuzzy (NF) modelling structures, and evolutionary optimisation with multi-objectives (real-time capable).

Abstract

The initial stage of this research investigation includes the creation of NF models, which accurately describe the behaviour of FSW in multiple scales, despite the availability of limited data. FSW, which is a solid-state joining process, is widely recognised in industry (aerospace, shipbuilding, automotive and railway) as an efficient, versatile and environmentally friendly welding technique that produces very high quality welds. Despite this success, many challenges are still ahead, due to the need for process certification and ISO standard compliance (reliable monitoring, and Non-Destructive Evaluation - NDE). A new model-based process monitoring and novelty-detection framework is proposed, it not only accurately monitors and predicts the process performance in real-time and in multiple scales, but it also provides a measure of assessing and predicting the normal or abnormal behaviours of the processes. In particular, this assessment is automatically communicated to the end-user via natural language feedback which is based on Human-Centric System (HCS). This is achieved by mathematically linking a number of process performance indices to a Fuzzy Logic rule base. The end-user reads (automatically generated text) the process performance in terms of forecasted product quality, reliability of model prediction, detection of abnormal behaviour, and overall multiscale process performance. The proposed model-based monitoring and novelty detection system is then coupled with a real-time capable multi-objective optimisation technique: a micro-Genetic Algorithm (micro-GA). For the first time in this field the multiple scales of FSW such as cooling rates, microstructure, mechanical performance, and overall quality of the manufactured parts are optimised in real-time using the proposed approach. The real-time processing capability is achieved by introducing short-length encoding for the micro-GA. The proposed model-based approach covers the whole manufacturing process lifecycle for FSW: process forecasting, monitoring-NDE and optimisation, while it is also generic enough to be employed in other manufacturing processes too, following further development.

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List of Abbreviations and Acronyms

A

ANFIS - Adaptive-Network-based Fuzzy Inference System, 46

ANN - Artificial Neural Networks, 3

ANOVA - Analysis of Variance, 37

ARTEMIS - Advanced Rotating Tool Environment Monitoring and Information System, 33

C

CFD - Computational Fluid Dynamics, 2

CI - Computational Intelligence, 2

D

DOE - Design of Experiments, 32

F

FCM - Fuzzy C-Means, 118

FE - Finite Element, 2

FFT - Fast Fourier Transform, 7

FL - Fuzzy Logic, 3

FSW - Friction Stir Welding, 1

G

GA - Genetic Algorithms, 3

H

HAZ - Heat Affected Zone, 21

HCS - Human-Centric Systems, 5

I

IMMPETUS - The Institute for Microstructural and Mechanical Process Engineering at The University of Sheffield, 7

M

micro-GA - micro-Genetic Algorithm, 8

MOGA Multi-Objective Genetic Algorithm, 51

MSE - Mean Square Error, 138

N

ND - Novelty Detection, 8

NDT - Non-Destructive Testing, 16

NF - Neural-Fuzzy, 3

NN - Neural Networks, 3

NSGA-II - Non-dominated Sorting Genetic Algorithm II, 51

P

POW - Process Operating Window, 4

List of Abbreviations and Acronyms

R

RBF - Radial-Basis-Functions, 7

RMSE - Root Mean Square Error, 76

ROA - Reduction of Area, 7

S

SVM - Support Vector Machine, 3

T

TMAZ - Thermomechanically Affected Zone, 21

TWI - The Welding Institute Ltd., 14

U

UTS - Ultimate Tensile Strength, 7

V

VEGA - Vector Evaluated GA, 51

W

WQ - Weld Quality, 7

Y

YS - Yield Strength, 7

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1 Introduction

Overview

Friction Stir Welding (FSW) is a solid-state joining process, widely recognised in the industry as an efficient, versatile and environmentally friendly welding technique that produces high quality welds (Booth, Jones, and Threadgill, 2006; "Friction Stir Welding - Benefits and Advantages," n.d.; Nandan, Debroy, and Bhadeshia, 2008; Threadgill, Leonard, Shercliff, and Withers, 2009). FSW has been routinely implemented as a manufacturing process in various sectors of industry such as aerospace, shipbuilding, automotive and railway (Colligan, 2004; Ding et al., 1994; Elvander, 2009; ESAB, 2010; Kallee and Mistry, 1999; Kallee, 2010; Mendez and Eagar, 2001). The impact and contribution of FSW for joining technology has been considerable over the last two decades and outstanding efforts have been made to improve this welding technique and its applications. There are, however, significant challenges still ahead to further understand the complexities of the process and develop the full potential of this welding technique. From a research perspective FSW is an exciting area to investigate due to its potential on applications and mainly to cover the huge demand from industry of new technologies to reduce costs of the process. The quality of welds produced with FSW is certainly one of the major advantages of the process, but the cost of tests to identify defects on welds is high and implies destroying the tested material. There is also a lack of development of techniques which can predict, analytically or otherwise, the behaviour of welds or analyse the FSW process in real-time.

Over the years, many researchers have proposed a variety of techniques to elicit advanced mathematical models that can replicate the physical behaviour of complex systems such as FSW. These models are commonly proposed as methods to reduce expensive experiments (Bhadeshia, 2008), and are used as tools to gain deeper understanding of complex systems. Numerical-based techniques such as Finite Element (FE) and Computational Fluid Dynamics (CFD) are approaches widely use to model the complex interactions found in FSW (He, Gu, and Ball, 2014). However, one of the main drawbacks of these techniques is the difficulty in expressing complex systems in simple models and from the point of view of real-time and online monitoring applications of industrial processes, these numerical-based modelling techniques cannot be used due to their high computational cost. Another significant challenge for the modelling of FSW is the limited experimental data available. It is expensive to generate dataset of welds to create a high quality dataset, and furthermore the analysis of mechanical properties and microstructure of the samples is also expensive and time consuming. Therefore, the available datasets for FSW are not in the hundreds or thousands of samples as in some other manufacturing processes.

To address the aforementioned challenges, this investigation proposes the use of mathematical models based on data-driven approaches. These modelling techniques are generally focused on: analysing information that represents the behaviour of complex systems, and determining the mapping relationship between the variables which are involved in the process such as inputs, internal variables and outputs. Data-driven models attempt to describe complex systems without including prior explicit knowledge of their physical behaviour. Another benefit of these modelling techniques is the ability to describe complex systems even with small datasets. These approaches have been developed with the contribution from data mining, pattern recognition, Computational Intelligence (CI), machine learning and other artificial intelligence paradigms. Data-driven modelling approaches are widely used in material science and engineering. The several data-driven modelling methods which have been used in these areas include Artificial Neural Networks (ANN), Fuzzy Systems, Genetic Algorithms (GA), Support Vector Machine (SVM), Gaussian process, and Bayesian, among others (Moraga, 2005; Solomatine, See, and Abrahart, 2008).

This thesis focuses on data-driven modelling based on CI paradigms, namely, Neural Networks (NN), Fuzzy Systems, and GA. NN's have the ability to learn complex nonlinear input-output relationships and combined with Fuzzy Systems, transparent models can be developed. Other benefits are the interpretability of the models, high accuracy and lower computational cost, when comparing with numerical based modelling approaches such as FE and CFD. GA are population-based evolutionary systems with the ability to solve single-objective and multi-objective optimisation problems. This thesis takes advantage of the best characteristics of each CI technique to create intelligent hybrid models. These models can efficiently analyse and predict the performance of complex industrial processes; create new model-based process monitoring methods; and, for the first time in this field, optimise in real-time the process' performance.

NN have the ability to approximate a function; however, to translate the results in terms of natural language it is possible to use fuzzy logic-based systems. Fuzzy Logic (FL) provides the computational framework for embedding structured human knowledge into workable algorithms. The main advantage of FL systems, for modelling approaches, is their transparency and interpretability of the models using linguistic variables. FL models extract knowledge from data which can then be presented in linguistic terms similar to human-based reasoning: IF THEN rules. A highly efficient hybrid approach is Neural-Fuzzy (NF) modelling which is a combination of NN and FL systems. NF modelling has been extensively used to accurately describe and predict the behaviour of complex systems. However, one of the main challenges in CI-based modelling for complex manufacturing process is the interaction with humans who are mostly non-experts. There is a need for developing Human-Centric models which can naturally interact and communicate unexpected behaviour from the system to the user (Pedrycz and Gomide, 2007b).

The use of modelling techniques in FSW has also assisted in the identification of the optimal Process Operating Window (POW). The definition of the optimal POW offers significant information on the process which can be used to better understand the process and accurately set up the process parameters. The identification of POW depends mainly on the material to be welded and tool design. This means that POW's are specific to the applications at hand. To date, the design of POW has been carried out mainly based on experimental trials and using expert knowledge, which is usually expensive. During this research investigation, modelling techniques were used as a tool to efficiently identify POW at the different scales of the process. Currently, multiscale modelling as a technique for studying complex systems is a significant tool for developing advanced engineering and materials science applications. The use of multiscale modelling has become widespread for analysing complex engineering systems (Fish, 2009, 2014; Groen, Zasada, and Coveney, 2014). This technique allows the study of multiple physical processes from a particular system. Multiscale models can capture multiple processes at different scales; each process is presented as a sub-model of the system. Multiscale simulations have been applied to a wide range of engineering problems. From the point of view of engineering and materials science applications, microscopic properties can be of crucial importance for the quality of the overall design of materials.

FSW is inherently multiscale; the process has been used in critical engineering applications; as a consequence, the multiscale analysis of FSW is important for the identification of defects or flaws. From the point of view of industry, it is particularly important to develop multiscale models of FSW, for example, to evaluate the final mechanical properties and microstructure of welds produced by FSW (Nandan et al., 2008). It is worth mentioning that for manufacturing applications, process experts often wish to determine the minimum or maximum values of the input process parameters at which the responses can reach their optimum. The design of systems which can find the optimal design for a set of given inputs (process parameters) allows insights into the underlying processes on its various scales. In this thesis, multi-objective optimisation addresses this challenge and more importantly, a real-time evaluation and optimal design of the FSW at its different scales is developed for the first time.

In this thesis, a data-driven modelling framework is proposed, focusing on real-time processing capability for FSW which is a highly complex thermomechanical process. Specific challenges that this research work addresses includes: availability of low number of process samples/data; modelling in multiple process scales (micro-, meso-, macro-); real-time processing capability (hence low computational cost); creation of new monitoring techniques capable of automatically identifying abnormal behaviour (novelty detection); and process optimisation that acts in real-time to ensure optimal POW of FSW at its multiple scales. A special research focus of the presented research work is Human-Centric Systems (HCS) in manufacturing, hence the aspects of natural language feedback to the user and simple (transparent to the non-expert) yet accurate models are also investigated.

The proposed hybrid model-based framework is based on Soft Computing, due to the need for system transparency and computational simplicity. This includes FL-based approaches as well as NF modelling structures, and evolutionary optimisation with multi-objectives which can be used in real-time.

1.1 Research aims and objectives

The aims of this research work and specific objectives are listed below:

i. Create data-driven models which can accurately describe and predict the FSW process while addressing the issues of:
   a. Low sample data size
   b. Multiscale approach
   c. Real-time forecasting capability
ii. Study the multiscale behaviour of FSW, by using simulations of the previously developed models, to gain further insights into the process, particularly in:
   a. Mechanical performance
   b. Microstructural composition
   c. Overall quality of the welds produced by FSW
iii. Take advantage of data from new monitoring techniques in the field, and create model-based approaches to understand such data and their use in reliable process certification.
iv. Create a model-based process monitoring framework that:
   a. Can forecast the process performance
   b. Embed 'Novelty Detection' within the monitoring regime by assessing abnormal process behaviour
   c. And communicate any results using natural language (human-centric design)
v. Create a methodology for optimising the POW's in real time, while considering:
   a. Multiscale performance of multi-objective targets
   b. Evolutionary optimisation algorithms with real-time capability
   c. Model-based approaches based on the previously developed frameworks

1.2 Research Contributions

Multiscale data-driven process models, which describe and predict the FSW process, were developed using CI techniques. In particular, NF structures were created based on Radial-Basis-Functions (RBFs). The created models were then used to create new knowledge about the operating window of the process. The models developed allowed better understanding of this welding technique and the influence of various welding speeds and tools on the final part performance. As a result of their linguistic-based structure inherent to FL systems, the multiscale models are easy to understand for non-modelling experts. The micro-scale model predicts microstructure of the materials produced, at the centre of the welding zone, which includes the average grain size, and, for the first time in this field, the cooling rate which is measured behind the welding tool. The meso-scale simulation includes NF models, which predict several mechanical properties: Elongation, Reduction of Area (ROA), Ultimate Tensile Strength (UTS) and Yield Strength (YS). These characterise some of the mechanical performances of the welded parts. The macro-scale model was developed to predict the overall Weld Quality (WQ), of the welds produced by FSW, for this research project, the WQ was assessed by process experts. The majority of these NF models were presented in *The Institute for Microstructural and Mechanical Process Engineering at The University of Sheffield (IMMPETUS) Colloquium 2011* (Sheffield). The cooling rate NF model, along with the process optimisation work (see next section) will be submitted to an International Journal.

A significant contribution, based on data-driven modelling, to directly predict the WQ was the development of a model that makes use of spectral-temporal information from an advanced monitoring device that measures tool-bending forces. A crucial part of this modelling work was pre-processing of spectral-temporal information to create a set of important markers to use as inputs to the data-driven model. The approach relies on Fast Fourier Transform (FFT) to extract information from the spectral temporal signal of the tool bending forces. Two performance markers were created and then used to create an NF model, which directly predicts WQ. The hypothesis is that vibration signature and profile of the forces are linked to the tool's performance. As a result of this modelling work the monitoring system was proposed to be simplified, hence less expensive, by focusing only on the spectral signals as suggested by the developed model. The temporal-spectral analysis, the developed NF model, and simulation results were presented in the *IMMPETUS colloquium 2012* (Sheffield); the application of this approach for real-time applications was presented in the *9th International Symposium on Friction Stir Welding* on 2012 (USA).

One of the most significant contributions of this thesis is the creation of a new model-based computational framework for Novelty Detection (ND) in manufacturing processes by using Soft Computing approaches. In the proposed framework, the Fuzzy Entropy measure of an RBF modelling structure is used to identify new behaviour. This new behaviour is defined as the difference between the monitored signals and the forecasted behaviour by the data-driven models. The extracted information from the model also includes reliability of the system's prediction. A secondary significant contribution, of this ND framework, to the aims of this research work, is a text-based feedback which is presented in natural language sentences to communicate the process performance to the user. This feedback, hence addresses the development of HCS. Part of this ND framework was presented in the *7th IEEE International Conference Intelligent Systems IS'2014* (Poland). The concept of HCS for manufacturing process, which objective is to create systems that can naturally communicate with the user, was presented in *The University of Sheffield Engineering Symposium (USES)*, 2013. A special presentation of this topic for FSW of aluminium alloys and steels was also given in the *3rd EPSRC Manufacturing the future National conference*, 2014 (Edinburgh).

In terms of optimising the process in real-time, the key research aspects were multi-objective optimisation of the multiple scales, and computational efficiency. A new model-based multi-objective optimisation framework is proposed based on the combination of a constraint micro-Genetic Algorithm (micro-GA), and an RBF-based model. It was found that by using the proposed approach, it is possible to find optimal welding parameters such as tool rotational and traverse speed within a strictly constrained search space, and for the first time, the trade-off between the various mechanical properties (elongation, ROA, UTS, and YS) and weld quality was studied. Similarly, the micro-scale performance of the FSW was investigated for the trade-off between microstructure (average grain size, cooling rate) and weld quality. The main results produced in this framework, including the optimisation work and resulting FSW-based simulations are in preparation for submission to an International Journal.

1.3 List of publications

Peer reviewed publications

i. Adriana Gonzalez-Rodriguez, George Panoutsos, Mahdi Mahfouf and Kathryn Beamish, ***A Novelty detection framework based on fuzzy entropy for a complex manufacturing process***, *Proceedings of the 7th IEEE International Conference Intelligent Systems IS'2014*, September 24-26, 2014, Warsaw, Poland, Volume 2: Tools, Architectures, Systems, Applications pp 453-464, 24-26, 2014. DOI: 10.1007/978-3-319-11310-4_39.

ii. Ali Baraka, Adriana A. Gonzalez-Rodriguez, George Panoutsos, Kathryn Beamish and Stephen Cater, ***Manufacturing Informatics and Human-in-the-loop: A case of study on Friction Stir Welding***, the *3rd EPSRC Manufacturing the future conference*, 23rd-24th September 2014, Glasgow, UK.

iii. A. A. Gonzalez-Rodriguez, G. Panoutsos, K. Sinclair, M. Mahfouf and K. Beamish, ***Model-based process monitoring in Friction Stir Welding***, Proceedings of the *9th International Symposium on Friction Stir Welding*, 15-17 May 2012, Alabama, USA.

Workshops and symposia

iv. A.M. Baraka, A. Rubio Solis, A.A. Gonzalez-Rodriguez, J.C. De Alejandro and G. Panoutsos, ***Human-Centric Approaches for Modelling Complex Processes***, *University of Sheffield Engineering Symposium (USES),* 20 May 2013, Sheffield, UK.

v. A. A. Gonzalez-Rodriguez, G. Panoutsos and M. Mahfouf, ***Model-based process monitoring in Friction Stir Welding via Spectral-Temporal analysis***, *IMMPETUS Colloquium 2012*, 3-4 April, Sheffield, UK.

vi. A. A. Gonzalez-Rodriguez, G. Panoutsos and M. Mahfouf, ***Multiscale modelling for industrial processes: a cross-validation study***, *IMMPETUS Colloquium 2011*, 19-20 April, Sheffield, UK.

1.4 Thesis outline

Chapter 2 emphasises the importance of FSW in industry, and demonstrates the benefits of applying advanced modelling techniques to study this process. This Chapter reviews literature regarding the three main concepts which underpin this thesis: the FSW process, computational modelling, and CI paradigms. The Chapter introduces the basic concepts of FSW, and modelling approaches used to model this process. Surveys of current research in the area of CI-based modelling of FSW are also presented.

Chapter 3, multiscale modelling is proposed to study the FSW at its different scales: micro-, meso- and macro-. Several data-driven models are elicited to predict mechanical properties, microstructure and weld quality of the system. Each model represents individual behaviour of the whole FSW welding routine. In this Chapter, for the first time, an NF-based model which extracts thermal information from the welding routine is created. This NF predicts the cooling rate of the process, which is an important property that has great influence over the final properties of the materials welded by FSW.

In Chapter 4, an NF model-based spectral analysis is proposed by using FFT to study internal variables of the FSW. The spectral analysis is proposed to correlate the signals of the process with quality performance. For the first time, two indices extracted from the spectral signal are developed to predict the weld quality of the system. A single-objective GA optimisation, which enhances the performance of the multiscale models, is also presented in this Chapter.

Chapter 5 presents a new ND framework which is created by taking advantage of the Fuzzy Entropy. The aim of this framework is to create a linguistic-based feedback mechanism which can advise the process users on the performance of complex manufacturing process. The main contributions of the proposed framework are (i) to warn the user when a new condition appears in the system, and (ii) to advise the user in regards to the reliability of the model's prediction when a novelty occurs. The proposed ND framework informs the performance of new behaviour in the system which can be linked to process variables affecting the quality of the joints. The information presented regarding the performance of the system is given to the user in a simple sentence.

In Chapter 6, a new multi-objective optimisation algorithm based on micro-GA and RBF is proposed. The algorithm extracts knowledge from previous NF models and integrates the experience from process experts to find the Pareto optimal solutions of two functions. The use of micro-GA was proposed in this Chapter because it is computationally inexpensive and is highly suited for real-time applications. The algorithm was applied to find the optimal speeds which satisfied certain requirements from the user such as specific mechanical properties, microstructure and quality of the weld. The optimal solutions produced by the proposed multi-objective optimisation may be helpful as a tool for decision support and can be used for the design of optimal POW for FSW. The optimisation framework presented in Chapter 6 may be used as part of complete process optimisation system including predicting, monitoring, evaluating, and optimising the multi-objective problems presented in the FSW manufacturing processes.

2 Friction Stir Welding and Computational Modelling

Overview

The success of FSW is evident by the number of industrial applications and the wide use of the process with aluminium alloys as well as a variety of other materials. This success has allowed the use of the FSW process in the manufacturing of critical components, for example, components found in the aerospace, automotive and rail industry (Colligan, 2004; Ding et al., 1994; Elvander, 2009; ESAB, 2010; Kallee and Mistry, 1999; Kallee, 2010; Mendez and Eagar, 2001). FSW is versatile, environmentally friendly, and the mechanical properties of the materials welded are good, this is a result of the plastic deformation of the materials (Nandan et al., 2008). Despite its success, due to the high complexity of the FSW process, significant challenges still ahead to further understand the behaviour of the process and develop effective models that can provide comprehensive understanding of this complex manufacturing process. Modelling techniques have been used to describe and predict certain behaviour of the process. The objective of this Chapter is to emphasise the importance of FSW in industry, and to demonstrate the benefits of applying advanced modelling techniques to study this process. This Chapter reviews literature regarding the three main concepts which underpin this thesis: the FSW process, computational modelling, and CI paradigms. The Chapter introduces the basic concepts of FSW, and then a review of modelling approaches used to model FSW is presented. Fundamental concepts of CI are described, and a description of selected CI paradigms used to analyse complex data and create intelligent models is detailed. Finally, a survey of current research in the area of CI-based modelling of FSW is presented.

2.1 The FSW process

2.1.1 Background and principle of operation

FSW is an efficient solid-state welding process for the joining of difficult-to weld materials and was invented in 1991 by Wayne Thomas at The Welding Institute (TWI) in Cambridge UK (Thomas et al., 1991). The FSW process represents one of the major advances in welding technology and since its discovery FSW has been widely adopted by various industry sectors such as aerospace, shipbuilding, automotive and railway. This welding technique has been used to join materials for critical applications; its impact in industry is reflected in the innumerable applications that have been developed (ESAB and Stevetsaren, 2009). This welding process is versatile, environmentally friendly and its implementation is lower in cost when compared with traditional welding techniques (Thomas, Woollin, and Johnson, 1999). The process was originally implemented to join aluminium and its alloys, however, due to its versatility and exhaustive research efforts over the years, its use has been extended to a variety of materials such as magnesium, copper, titanium, steel and even polymers (Nandan et al., 2008).

The basic principle of the FSW process is shown in Figure 2.1 and consists of a non-consumable rotating tool with a shoulder and a profiled probe. The probe is inserted between the two work pieces to be welded. These two pieces of material are rigidly held while the rotating tool is pressured downwards until it makes contact with the material surface and rotates moving across the joint line. The friction caused by the rotating tool generates heat between the tool and the materials being welded. The probe stirs the material, transforming it from solid-state into plastic-state, merging both materials to create the joint. The material where the direction of the rotation is the same as the welding direction is known as *advancing side*, and the material where the direction of the tool rotation is opposite to the welding direction is known as *retreating side*. As the process takes place below the melting point of the materials, FSW conserves the metallurgical properties of the materials joined. This results in high quality welds with excellent mechanical properties in fatigue, tensile and bend.

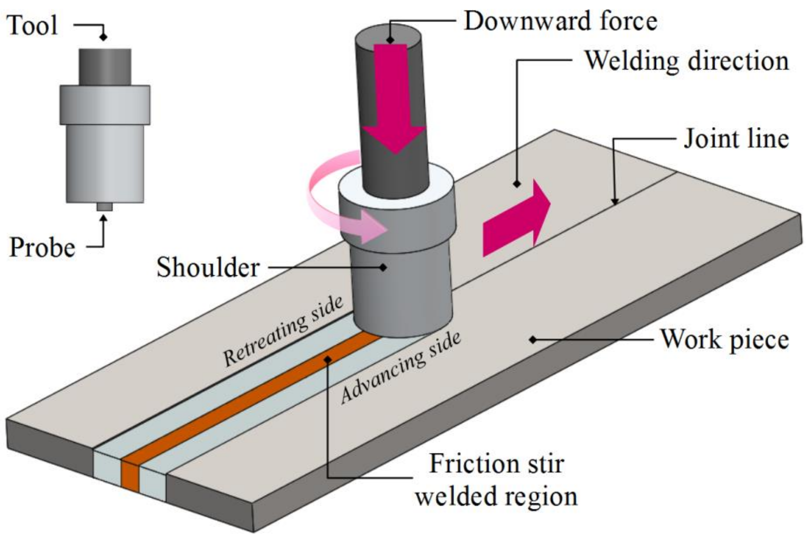

Figure 2.1 Schematic diagram of the FSW process (Thomas et al., 1991)

FSW has gained a reputation within the welding community as an easy and defect-free process. However, as presented in (Nandan et al., 2008), the physical phenomena involved during the process, including material flow, complex interactions between the tool and workpiece, heat generation, and plastic deformation, as well as the influence that process parameters (such as rotation speed, traverse speed and downward force) have over the process, are factors that make this simple welding technique a complex non-linear process, which is not easy to understand.

The great interest from industry to develop new technologies using FSW and to thoroughly understand the FSW process has encouraged the research field for this welding technique. As a result, over the past two decades, significant contributions have been made in different fields related with FSW technology and development of new applications. For example, more advanced welding tools have been developed and their influence over the process has been evaluated (Thomas, Nicholas, and Smith, 2001a). The range of materials that can be welded has been extended beyond aluminium alloys (Çam, 2011; Nandan et al., 2008). Automation of the process and production is nowadays ordinarily used in industry (ESAB, 2010), at the same time, data acquisition systems have been developed to record the process variables and guide the knowledge about the welding technique (Beamish and Russell, 2010a).

The development of Non-Destructive Testing (NDT) techniques and quality control systems in FSW is an area of great interest and potential for new discoveries (Kinchen, Martin, Space, Orleans, and Aldahir, 2002; Zappia, 2010). In recent years, there has been an increasing amount of research efforts to deeply understand the physical phenomena present during the FSW process and simulate its behaviour, especially from the point of view of materials science (Nandan et al., 2008). However, as previously explained, due to the complexities of the process (e.g. material flow, heat generation, plastic deformation etc.), many challenges remain, including the development of intelligent and transparent process models, as well as monitoring and real-time systems that can provide accurate feedback of the process' performance. This thesis will focus particularly on the challenges related to the development of new computational models and novel intelligent systems that can monitor the process in real-time, evaluate its performance and produce useful information for the experts and final users.

2.1.2 Industrial applications

Certainly, the manufacturing processes using FSW have become more efficient, FSW has contributed to the development of new manufacturing technologies. Its impact can be illustrated in the many industries that are now using the process. This Section will present some of the crucial applications that have been adopted for various industry sectors. The literature presented here reflects the influence that FSW has had in the development of new technologies. The process was first commercially available in the late 1990s, when shipbuilding and aerospace industries realised the benefits of using FSW to produce high quality welds. In 1996, *Sapa* manufactured hollow aluminium for deep freezing of fish on fishing boats and panels for ship decks. The freezer panels opened up the commercialisation of FSW and eventually, the first vessel was built using friction stir welded panels made *by Marine Aluminium*. In 1998, the aerospace industry applied FSW to the space programs of Delta II rockets (Kallee, 2010). Since then, innumerable applications have been developed using this welding technique. Presently, a variety of aluminium alloys can be welded using FSW, including those that were difficult to weld (2xxx, 6xxx and 7xxx series) by conventional fusion welding techniques such as fusion-gas or electric arc. The process has also been adopted for welding magnesium, titanium, copper and steel alloys among other material, detailed research about these materials is presented in (TWI Ltd., 2013). With regard to cost savings and improvements in fabrication, the use of FSW has been significant for high investment industries. For example, *The Boeing Company* reported that by using FSW for the design of satellite launch rockets (Delta IV and Delta II) they have achieved a 60% cost saving and the reduction of manufacturing time from 23 to 6 days (TWI Ltd., 2001). Different industry sectors have thus benefited with the implementation of FSW some crucial applications among these sectors are presented over the following paragraphs.

Shipbuilding

As noted above, the industrialisation of the process started within the shipbuilding sector. Since then, FSW has become a normal and cost-effective industry practice to produce prefabricated panels of various types and sizes to build fishing boats, high-speed ferries and sea vessels. In 1996, for the first time *Sapa* applied FSW to manufacture hollow aluminium freezer panels for fishing boats. At the same time, deck panels and helicopter landing platforms were produced at *Marine Aluminium*. In this sector, the process was also used for the following applications: ship and oil-rig panels for decks and bulkheads, vessels, honeycomb panels and corrosion resistant panels, deck panels for civil and naval ships, hulls and superstructures; extended information about these applications is presented in (Kallee, 2010).

Aerospace

The Boeing Company was a pioneer in introducing FSW to the aerospace industry. They demonstrated the benefits of adopting FSW for their space programs *Delta II* and *Delta IV*. In 2001 *Boeing* reported the production of more than 3000 metres of defect free friction stir welds, with cost savings of 60% and an enormous reduction in manufacturing time (TWI Ltd., 2001). The FSW process offers considerable potential for low-cost joining of lightweight aluminium airframe structures for large civil aircraft such as the Airbus A380. It is also used in the production of light aircraft such The Eclipse 500 business jets, manufactured by *Eclipse Aviation*. Another example of aluminium alloys welded by FSW to reduce weight components was developed at *NASA's Marshal Space Flight Center*, the shuttle's super lightweight tanks were welded using FSW, in this way it was possible to significantly reduce the weight of the external tank by 3,402 Kilograms (Kallee, 2010). As presented in (TWI Ltd., 2013), the FSW process for the aerospace sector can be also considered for applications in: air fuselages and wings, empennages, cryogenic fuel tanks for space vehicles, aviation fuel tanks, external thrown-away tanks for military aircraft, military and scientific rockets, and the repair of faulty MIG welds.

Railway

The railway industry has adopted the FSW process with great success building trains and trams using large panels made from aluminium extrusions and rolling stock panels welded by FSW. In 1996, single-wall aluminium roof panels for rolling stock applications were introduced by *Sapa* and Hydro *Marine Aluminium* for railway applications. In 1999, *Alstom LHB* used these prefabricated panes for

Copenhagen suburban trains and later, in 2001, they used friction stir welded aluminium side walls and floor panels for suburban trains in Munich. *Hitachi* has produced and exported a range of vehicles for commuter and domestic trains. *Light Metal Industries* produce floor panels for the *Shinkasen* network of high-speed railway lines in Japan. The use of FSW has, therefore, helped to achieve high standards of safety for high-speed trains (Kallee, 2010; TWI Ltd., 2013).

Automotive

The automotive industry has developed a wide range of car components of different thicknesses, shapes and materials using FSW. This sector is the best example of efficiency of the process for covering specific demands such as large manufacturing batches, six sigma requirements and material combinations. FSW is used worldwide in series production of aluminium automotive components such as light alloy wheels and fuel tanks. *Ford* in the USA applied FSW for the design of components used for the chassis in the *Ford GT* sports car. This application maximised the fuel volume and reduced the number of connections to the fuel system. Suspensions and pistons with excellent mechanical properties have also been produced using FSW. *Volvo*, *Saab*, *Audi*, *VW* and *BMW* use wheel structures in which cast or forged centre parts are friction-stir welded to the rims, reducing the wheel weight by 20-25% (Kallee, 2010). More examples of automotive applications include: engine and chassis cradles, truck bodies and tail lifts for lorries, mobile cranes, armour plates for vehicles, fuel tankers, caravans, buses and airfield transportation vehicles (Kallee, 2010; TWI Ltd., 2013).

Other applications

Notable benefits of the FSW process include cost savings, good repeatability, excellent mechanical properties and low distortion. The active evolution of advanced equipment to automate and control the process, as well as the efforts to weld materials with higher melting points and dissimilar material joints, have allowed the development of novel applications in other industry sectors. These include construction, housing, heating and air conditioning, and copper canisters for nuclear waste (Kallee, 2010). Additionally, FSW has successfully been applied to develop new technologies in consumer electronics such as the design of the *iMac* on 2012. *Apple* employed FSW to join the enclosure, achieving 40% less volume than previous *iMac* generations (Apple, 2012). The process has also been used for significant applications within the food industry; in 2004 *RIFTEC* started a series production of flaw-free drying trays and later they used FSW for the production of cooling plates for industrial plate freezing plants (RIFTEC, 2004), these applications show how FSW has helped considerably in reducing costs and producing lighter components, as well as achieving higher hygiene standards (RIFTEC, 2004).

This Section was presented with the aim of illustrate the global impact that FSW has had over industry since its first commercial application. The benefits in terms of cost, weight reduction and quality of products show the potential of this welding technique and the clear motivations to invest on research and develop new and more advanced technologies.

2.1.3 Metallurgy: The FSW zones

The friction stir welded region has a number of different zones that are thermally and mechanically influenced during the welding process. Several studies have revealed that this influence defines the microstructure of the weld and thus the properties of the joint (Beamish and Russell, 2010a, 2010b; Beamish, 2007; Bhadeshia and DebRoy, 2009; Nandan et al., 2008; Threadgill et al., 2009). For aluminium alloys, the final microstructure could be divided into four distinct regions, as shown in Figure 2.2:

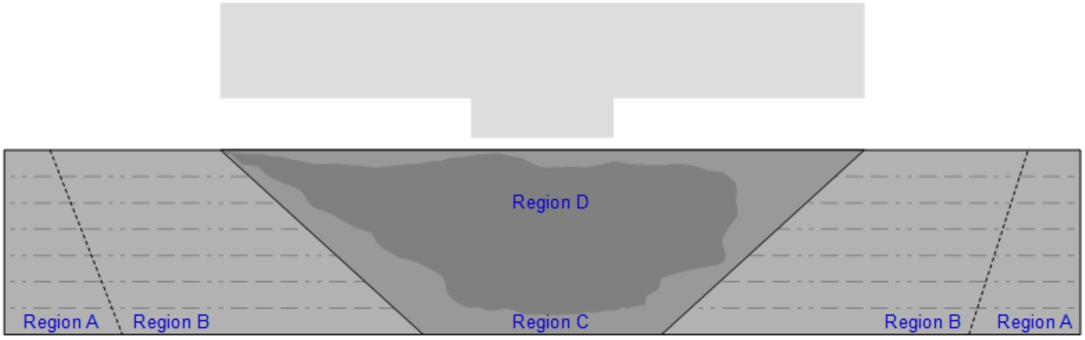

Figure 2.2 Schematic cross–section of a typical FSW weld for aluminium alloys showing four distinct regions (TWI Ltd., 2013)

According to (TWI Ltd., 2013), the four regions identified can be described as follows:

A. Parent material: the parent material is the material outside the influence of the welding process and its properties are completely unaffected.
B. Heat Affected Zone (HAZ): the HAZ is the material adjacent to the weld. In this region, clearly closer to the weld centre, the material experiences a thermal cycle, which modifies the microstructure and mechanical properties. There is, however, no plastic deformation of the material in this area
C. Thermomechanically Affected Zone (TMAZ): this region exhibits both thermal and mechanical energy input, and is therefore, subjected to both heating and deformation.
D. Nugget: the nugget is a region where the material is exposed to high temperatures and severe deformation, resulting in recrystalisation in the grain structure.

Heat generation in FSW

The plastic deformation of the process involves complex thermomechanical dynamics generated mainly by the frictional heating produced between the shoulder and the material surface. The plastic flow of the material depends on the heat generation. These factors, heat generation and material flow, determined the mechanical integrity of the joint. Detailed insights into heat generation and its influence in the final microstructure of welds produced by FSW for aluminium and other materials are presented in (Nandan et al., 2008).

2.1.4 Process variables

FSW is in essence an easy to implement process, but its thermomechanical behaviour involves complex interactions. These interactions affect several phenomena including: the heating and cooling rates, plastic deformation, plastic flow, and dynamic recrystallization. These phenomena interactions, which reflect the mechanical integrity of the joint, are very difficult to study (Nandan et al., 2008). It is, however crucial to understand the effect that all these factors have over the process as this influence will determine the outcome of the welding process.

The main variables used to control the FSW process are listed in Table 2.1. The primary variables have the most significant influence over the process. The secondary variables can be measured and provide important information regarding the process. Previous research findings have proven that the tool design has a significant effect on material flow behaviour (Beamish and Russell, 2010b; Beamish, 2007; Thomas, Nicholas, and Smith, 2001b). A summary of tool design variables and other external variables that have influence over the process is shown in Table 2.2.

Table 2.1 Main FSW process variables

Primary variables	Secondary variables
Tool rotational speed	Spindle torque
Tool traverse speed (welding speed)	Traverse force
Tool plunge depth	Lateral force
Tool tilt angle	Tool temperature
Tool down force	Workpiece temperature

Table 2.2 Tool design and other FSW process variables

Tool design	Other
Shoulder and probe materials	Anvil material
Shoulder diameter	Anvil size
Probe diameter	Workpiece size
Probe length	Workpiece properties
Thread pitch	
Feature geometry	

An example of the two primary FSW parameters (tool rotational speed and traverse speed) and their influence upon the process is illustrated in the optimal POW Figure 2.3 (TWI Ltd., 2013). The definition of the optimal POW offers significant information about the process, this information can be used to better understand the process and accurately set up the parameter process. For example, it is well known that slow tool rotational speeds are insufficient to generate heat and plasticise the material, this results in poor performance of the welding process. By increasing the tool rotational speed, the plasticisation of the material is facilitated producing good welds, the use of POW allows a better understanding of the speeds applied and its limits, reducing the physical trial and error experiments.

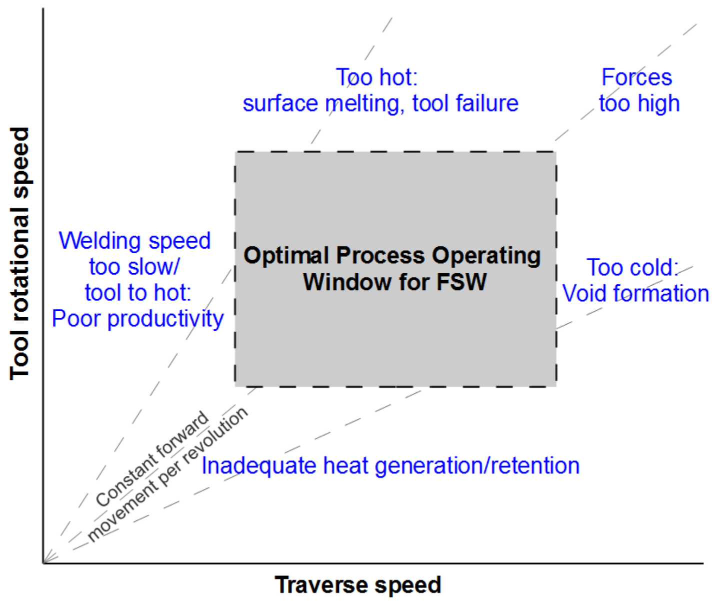

Figure 2.3 Process operating window for FSW based on tool rotational and traverse speeds (TWI Ltd., 2013)

The tool traverse speed and forces applied during the process are also of significant influence over the final quality of the welds. For example, at slow traverse speed (e.g. 280 mm/min for AA5083 material), the heat gradually increases around the tool, hence, the tool can steadily move and soften the material. As a result, the forces applied to move the tool across the weld are generally low. As the tool traverse speed increases, the plasticisation of the material around the tool decreases, the increase of rotational and traverse forces is required to move the tool. Eventually, if the tool traverse speed is excessively high (e.g. 812 mm/min for AA5083), there is insufficient time to heat up the material. This can result in forming a harder material, consequently, the tool cannot move, generating a failing welding process and also damaging the tool (TWI Ltd., 2013).

2.1.5 Tool design

Tool design is crucial in the FSW process due to its influence to generate heat and facilitate the material flow. Investigations have revealed that the shoulder produces most of the heat and the material flow is affected by the influence of both, the shoulder and the probe. Extensive research has demonstrated the importance of tool design to achieve good mechanical properties. Several new features, such as tool pin shape and pin angle, have been developed to improve the design of FSW probes and create more advanced and efficient tools (Beamish and Russell, 2010a, 2010b; Beamish, 2007; Nandan et al., 2008; Perret, Martin, Threadgill, and Ahmed, 2007; Thomas et al., 2001a). Tools used for FSW aluminium alloys are generally made from steel such as AISI H13, or, the cobalt-nickel-chrome superalloy MP159. The *MX Triflute™* and *MX TriFlat™* are advanced probes that have been used routinely for welding specific alloy types and thicknesses (Beamish and Russell, 2010a). This thesis introduces only the information and characteristics of *MX Triflute™* and *MX TriFlat™* due that the experimental data used for this research work was produced by using either of these tools.

MX Triflute™

The *MX Triflute™* probe shown in Figure 2.4 (TWI Ltd., 2000) moves less material than a cylindrical pin type probe, allowing a more efficient flow path. The helical ridge around the flute helps to disperse surface oxides (Thomas et al., 2001a; TWI Ltd., 2013).

MX TriFlat™

The three flat surfaces of this tool enhance the flow of material around the tool and assist the plasticisation of the material (see Figure 2.5).

Figure 2.4 The MX Triflute™ probe

(TWI Ltd., 2013)

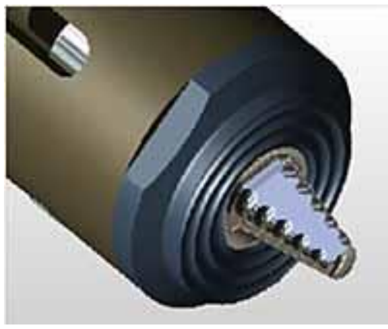

Figure 2.5 The MX TriFlat™ probe

(TWI Ltd., 2013)

These tools have been proven to be effective over a wide range of welding parameters for most grades of aluminium alloys, applications using these tools are reported in (Perret et al., 2007; TWI Ltd., 2013).

2.1.6 Concise advantages of the FSW process

The advantages of the FSW process result from the fact that the welding takes place in a plastic state without melting the materials to be joined and consequently retaining a great proportion of the properties of the welded materials. According to the literature studied, the major benefits of the FSW process can be summarised as follows ("Friction Stir Welding - Benefits and Advantages," n.d.; Ma, 2008; Threadgill et al., 2009; TWI Ltd., 2013):

i. High quality welds: compared with fusion welding techniques, the plastic deformation that materials welded by FSW suffer does not dramatically change the microstructure and keeps the mechanical properties of the materials, resulting in high quality welds.
ii. Production of defect-free welds: FSW eliminates defects such as solidification cracking, liquation and porosity associated with fusion welding techniques.
iii. Join of materials difficult to weld: FSW has the ability to join materials that were impossible or difficult to weld by fusion welding techniques, for example, series 2XXX and 7XXX of aluminium alloys, as well as magnesium and copper.
iv. Easily automated process: the process is suitable for automation and is adaptable for robotic use, reducing the degree of operator skill required.
v. Green and energy-efficient: FSW produces relatively low noise levels, also non-consumable or gas shielding is required.
vi. Safe welding process: staff safety is enhanced as no toxic fumes or radiation is generated during the process.
vii. Not only aluminium: FSW has been successfully applied to weld a variety of materials such as magnesium, titanium, copper and steel.
viii. Only few parameters to control: the major parameters affecting weld quality are tool rotational speed, tilt angle and tool shoulder.
ix. FSW can be used in any orientation without regard to the influence of gravitational effects on the process.

2.1.7 Potential flaws and defects in welds produced by FSW

Even though FSW is a very constant process, the generation of flaws and defects can appear, producing imperfect welds. As explained in (Threadgill, 2007; TWI

Ltd., 2013), it is important to differentiate between flaws and defects in a weld. The author's concepts of flaw and defect in welds produced by FSW are defined as follows:

A flaw is an unintentional imperfection in a welded structure which may or may not compromise the integrity of the structure. After a critical assessment, it could be regarded as a defect, or accepted as a tolerable flaw.

A defect is an imperfection in a weld whose presence cannot be tolerated. It must be removed or other remedial action taken.

In accordance with (Threadgill, 2007), the flaws found in friction stir welds can be categorised as volumetric flaw and joint line flaw. Volumetric flaws are caused by a lack of material consolidation. A joint line flaw is a joint line remnant produced for oxide particles delineating the original joint-line. A different categorisation of defects is given by (Zettler, Vugring, and Schmucker, 2010) where the author presents an extensive analysis of defects. He classified the defects as: defects from too hot welds, defects from too cold welds, and defects from geometrical mistakes. Common imperfections that can be found in aluminium alloys welded by FSW are summarised in Table 2.3. A detailed assessment of flaws in fiction stir welds for this material can be found in (Threadgill et al., 2009).

Table 2.3 Summary of common flaws encountered in FSW for aluminium alloys

Flaw type	*Location*	*Causes*
Void	Advancing side at the edge of the weld nugget	Welding speed to high Plates not clamped close enough together Reduction of force pressure
Void	Beneath top surface of weld	Welding speed too high
Joint line remnant	Weld nugget, extending from the root of the weld at the point where the original plates butted together	Inadequate removal of oxide from the plate edges Inadequate disruption and dispersal of oxide by tool
Root flaw	Weld nugget, extending from the root of the weld at the point where the original plates butted together	Tool pin too short Incorrect tool plunge depth Poor joint tool alignment

2.1.8 Materials

Aluminium alloys

As noted earlier, aluminium and its different alloys are widely used in industry. Aluminium is a soft, lightweight, nonmagnetic, malleable metal with good resistance to corrosion, and good thermal and electrical conductivity. Its strength and other physical and mechanical properties including density, ductility, workability, weldability, and corrosion resistance can be improved with the addition of other elements and heat treatments (TWI Ltd., 1996, 2013).

Table 2.4 shows the classification of wrought aluminium alloys.

Table 2.4 Wrought aluminium alloys

Series	Alloying element
1000	Pure aluminium (Al)
2000	Aluminium alloyed with copper (Al-Cu)
3000	Aluminium alloyed with manganese (Al-Mn)
4000	Aluminium alloyed with silicon (Al-Si)
5000	Aluminium alloyed with magnesium (Al-Mg)
6000	Aluminium alloyed with magnesium and silicon (Al-Mg-Si)
7000	Aluminium alloyed with zinc (Al-Zn)
8000	Aluminium alloyed with lithium and others (Al-Li)

The weldability of materials is influenced by the different compositions and heat treatments of the aluminium alloys. Series 1xxx, 3xxx, 4xxx, 5xxx, and 6xxx can be fusion welded using TIG (Tungsten Inert Gas), MIG (Metal Inert Gas) and oxyfuel processes. Series 7xxx and most of the 2xxx are not suitable for fusion welding. As illustrated in Figure 2.6 (TWI Ltd., 2013), FSW can be used to weld many aluminium alloys, including those which are not possible to weld when using other fusion welding techniques (TWI Ltd., 1996). Series 5xxx have excellent weldability and good corrosion resistance; series 6xxx are widely used for their strength.

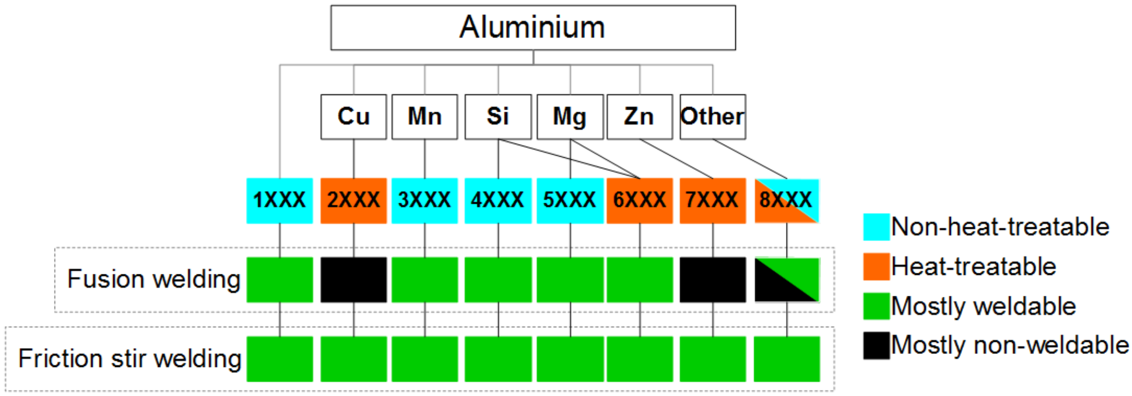

Figure 2.6 Weldability of aluminium alloys FSW vs. Fusion welding (TWI Ltd., 2013)

The heat input and cooling rate associated with the welding process can have significant effect upon the strength of aluminium alloys (Nandan et al., 2008; Thomas et al., 2001b). AA6082 and AA5083 are examples of aluminium alloys with excellent strength and good corrosion properties. AA6082 is aluminium alloyed with magnesium (0.7%), manganese (0.5%) and silicon (0.9%) which is more resistant to deformation. Depending on the heat treatment used; this aluminium alloy can have high strength, good weldability and reasonable resistance to corrosion. AA6082 is widely used for general and structural engineering applications where good strength and formability are required. This alloy is one of the most frequently used. The 6xxx series of aluminium alloys are particularly suited for FSW and have a very wide POW. AA5083 is non-heat-treatable aluminium alloyed with magnesium (4.6%), manganese (0.6%) and silicon (0.3%) with high corrosion resistance; it is commonly used in high corrosion environment applications such as seawater. The 5xxx series of aluminium alloys have a smaller POW (TWI Ltd., 2013).

Several studies have examined in depth the effect that heat generation has over the microstructure and properties of friction-stir welded aluminium alloys (Çam and Mistikoglu, 2014; Kimapong and Watanabe, 2004; Nandan et al., 2008; Perret et al., 2007; Sivashanmugam, Ravikumar, Kumar, Rao, and Muruganandam, 2010; Threadgill et al., 2009). The most complete investigations of FSW in relation with aluminium are presented in (Nandan et al., 2008) and (Threadgill et al., 2009). Together, these studies provide important insights into FSW, particularly of aluminium alloys, and deeper knowledge regarding to their microstructure and mechanical properties.

Other materials

As explained above, FSW has successfully addressed the welding of aluminium alloys. The benefits demonstrated for aluminium can conservatively, be transferred in other materials including steel, titanium, copper, magnesium (Bhadeshia and DebRoy, 2009; Çam, 2011; Nandan et al., 2008; TWI Ltd., 2013), dissimilar alloys (DebRoy and Bhadeshia, 2010; Kimapong and Watanabe, 2004), and even thermoplastics (Buxton, 2002). The major limitation to transfer the FSW technology is the development of suitable welding tool materials. For instance, FSW of steel and titanium faces more difficult operating conditions as a result of the high melting point of these metals (Bhadeshia and DebRoy, 2009; Nandan et al., 2008). Aluminium is friction stir welded at between 300-400˚C and thus tools made from steel are generally adequate for the process. As the temperature of the workpieces rises, tools which can retain their properties at higher temperature are required. For example, the welding of copper alloys employs tools made from tungsten that can work at 600-900˚C. By contrast, FSW of steel requires a tool that can resists temperatures over 1000˚C (Bhadeshia and DebRoy, 2009; TWI Ltd., 2013). Nonetheless, FSW of steel and titanium are areas of active research, and despite the limited number of applications, in comparison with FSW of aluminium alloys, significant applications for FSW have been proposed (Bhadeshia and DebRoy, 2009; Çam, 2011; Perret et al., 2007).

2.1.9 Monitoring FSW towards a quality control

As explained earlier, FSW offers many advantages over conventional fusion techniques for joining aluminium alloys. The quality of welds produced by FSW is one of the main benefits of this welding technique; as a result, there is great interest from industries and FSW technology producers for developing more advanced monitoring tools and quality control systems. Major efforts have been made for developing NDT to detect flaws in welds produced by FSW (Kinchen et al., 2002; Zappia, 2010). At the same time, intensive research has been carried out to develop advance technology that can accurately record welding data during the FSW process. A comprehensive investigation of FSW tool design and its influence over the process was presented by (Beamish and Russell, 2010a). This study showed that the use of advance process monitoring systems for quality control of the FSW process is a crucial factor for the development of more advanced technology that can help to better understand the relationships of welding parameters, and their effects over the final product. The authors listed some of the benefits of using an advance monitoring system to meticulously investigate the FSW process:

i. Provide a degree of confidence that repeatable welds are being produced, especially for critical applications.
ii. Assist with the scientific understanding of process dynamics and tool performance.
iii. Assist with optimisation of tool designs and process parameters.
iv. Record data and provide feedback on the machine and process conditions.
v. Aid with the specification of new FSW equipment.

Hypothetically, the main purpose of using NDT techniques and advance monitoring systems is to create reliable quality control tools for FSW. At present, FSW machines have integrated data acquisition systems to measure and record process parameters. Usually, the parameters recoded are: rotational speed, traverse speed, tool position (x, y, and z), spindle torque, downward force, and tool temperature. However, little literature is available in regard to the use of these data acquisition systems and their application for quality control.

There is also, a research gap related to the integration of monitoring and control systems for applications in real-time, particularly, for developing advanced applications that are able to detect changes during the welding routine, evaluate the influence of these changes over the welds, and at the same time, adjust the process conditions in order to maintain the quality of welds.

At TWI Ltd., significant research has been carried out in relation to the development of technology that can record and monitor data during the FSW process. For example, (Blignault, 2008), presented a report that describes in detail the concept of quality control for FSW. In the report, the research related to the development of FSW monitoring technology is reviewed. More significantly, this study introduces the design of an advanced FSW monitoring system that is capable of recording data from the FSW process. The information recorded include: z-axis forces, torque, bending forces on the tool (x/y axis) and temperatures. The latter study, lead to significant findings in the area, Beamish and Russell (Beamish and Russell, 2010a), demonstrated that the use of this technology can assist experts in the study of the FSW process. They demonstrated that the analysis of the information recorded offers a better understanding about the influence of process conditions. In their research, the data acquired from the advanced monitoring system, was analysed to study the influence that tool design and other process conditions have over the microstructure of the material and the appearance of common flaws such as joint line remnant. The findings of this report in relation with tool design are summarised in Appendix 1, Table 9.1 and Table 9.2.

Further research in this area is presented in (Zappia, 2010), in which an approach based on Design of Experiments (DOE) for establishing requirements and develop a quality control system for FSW is described. The author explains that the clear definition of the initial weld requirements and control of process parameters (i.e. POW) are essential. They can be used as reference to inspect and measure weld quality. More importantly, the author presents an extensive survey of monitoring techniques and NDT approaches (offline). The monitoring techniques discussed are: real-time sensing of the FSW process parameters, weld temperature, weld path errors and visual monitoring of the weld. The author proposes these techniques as 'online' approaches which can be used to monitor the FSW process along with analytical sensing techniques. The author explains that the aim of these analytical sensing techniques is to find correlations between the data recorded and defects in welds, he presents examples of both 'online' and analytical sensing techniques. However, the examples are mainly theoretic and not specific for real-time applications. A summary of these online and offline techniques, and the challenges related with each technique are presented in Appendix 1, Table 9.3. The information in this table reveals the importance of developing more reliable monitoring and NDT techniques, especially to assess the FSW process in-real time.

2.1.10 An advanced monitoring system: The ARTEMIS tool

As mentioned in the previous Section, TWI Ltd. has contributed to the research and development of advanced monitoring technology for FSW. They designed an instrumented rotating tool holder (Figure 2.7) which has been used to quantify the effects of FSW tool features, and has helped to better understand the behaviour and performance of FSW tools under various welding conditions. This tool known as ARTEMIS (Advanced Rotating Tool Environment Monitoring and Information System) records process variables such as tool torque, tool temperature, tool axial loading (z-axis force) and tool lateral bending forces during the welding routine. This tool offers a high level of process information, especially, via the generation of 'footprint' plots that display the forces acting around the FSW tool (Figure 2.8). The ARTEMIS tool records force traces, providing information of bending forces every 7.5° intervals around the tool circumference (360°). An advanced data acquisition system is employed to characterise the tool bending forces and display this information on polar plots. This monitoring system has already provided significant information on the effects of tool profile which can potentially be correlated to weld quality and defect detection (Beamish and Russell, 2010a).

Figure 2.7 The ARTEMIS tool

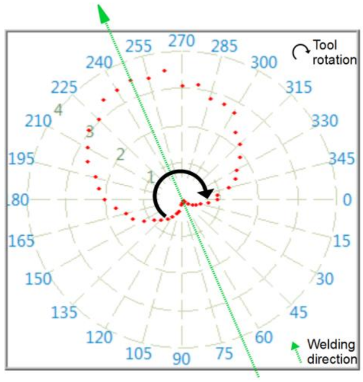

Figure 2.8 Polar plot of bending forces

In general, the potential benefits of using advanced tools such as ARTEMIS, to collect process data, and analyse the welding process information can be summarised as follows:

i. Help in finding input-output relationships, of the recorded data, to predict weld joint strength and weld properties during the weld process.
ii. Assist in better understanding of tool performance.
iii. Provides insights into the tool/workpiece complex interactions.
iv. Assist in establishing the reliable use of POW in relation to force, torque and temperature measurements.
v. Potential to evaluate quality of the welds for real-time applications.
vi. Assist the development of quality control methods that can identify and correct process variations before the formation of flaws.
vii. Develop intelligent control systems that can optimise the process parameters.

In general, one of the main drawbacks in the area of monitoring and analysis of FSW, is the lack of approaches that can provide transparent information about the process in real-time. Another topic to address is the development of monitoring systems that can evaluate the properties and quality of the welds during the welding routine.

The literature presented in this Section aims to demonstrate that advanced monitoring systems such as the ARTEMIS tool can be used to assist the development of more advanced approaches for quality control. The literature review presented in this Section, reveals that the process information provided by the ARTEMIS tool can be used as knowledge to develop intelligent and efficient applications. These applications can, potentially, monitor and identify problems during the welding process. Over the years, many researchers have proposed a variety of techniques to create advanced mathematical models that can replicate the physical behaviour of complex systems such as FSW. These models are commonly proposed as methods to reduce expensive experiments (Bhadeshia, 2008), and are used as tools to gain deeper understanding of complex systems. In the following Section, this topic is reviewed in detail.

2.2 Mathematical modelling of FSW

Background

The use of mathematical models has been widely applied in physics, economics, life science, engineering and many other disciplines, in order to more clearly understand and replicate the behaviour of complex real-world systems. Materials science has taken advantage of modelling techniques to predict mechanical behaviour of metals, estimate complex properties of materials and to better understand the material's structure at both micro and macro levels. Modelling in materials science has grown significantly over the past two decades; mainly as a result of the interest from various industries. Their aim is to achieve better solutions for their systems by minimizing the use of resources. Modelling techniques are proposed as a reliable alternative to reduce experimental testing that involves the destruction of materials. In addition, modelling has gained considerable success in developing computational tools that can predict the behaviour of materials and avoid the formation of some defects. Significant evidence of this success has been published over the last decade (Bhadeshia and Honeycombe, 2006; Elangovan, Balasubramanian, and Babu, 2009; Nandan et al., 2008). In general, major contributions have been made in the mathematical modelling of materials science, new technologies and materials have emerged as a result of these contributions. As (Bhadeshia and DebRoy, 2009) point out, there has been much progress and success in modelling in materials science. Despite this, however, there are still certain limitations regarding the development of mathematical models. In terms of data available, scientists can face major challenges when attempting exploit large amounts of data, and at the same time take advantage of all the collected system's information. The complexity of systems usually increases the complexity of the models, making it difficult for scientists to translate the knowledge of the model to non-experts, and take full advantage of these modelling techniques. As a result of these issues, namely, large quantities of data and complex systems, the computational cost to produce these models is usually high. Additional drawbacks of mathematical modelling are: the understanding of uncertain behaviour; the presence of noise in data and the integration of models that can adapt knowledge from process experts. Indeed, many approaches have been proposed to develop more advanced modelling techniques that can deal with these drawbacks. Since the invention of FSW, most approaches for modelling FSW have proposed the use of numerical analysis to develop more advanced models. As introduced in Chapter 1, the use of CI is proposed in this thesis as an alternative to model this welding technique, and to develop data-driven models which can learn from process data. The following Section will briefly introduce the use of numerical analysis approaches that have been implemented to model the FSW process. Further, in this Chapter, a review of the approaches proposed to model FSW, based on CI, will be presented.

2.2.1 Numerical modelling approaches for FSW

Numerical analysis of FSW has played a significant role in the progress made in understanding the FSW process: the simulation of properties of the resulting friction stir-welded joints, and the evaluation of the influence that process conditions and tool design have over the process. This progress is the result of exhaustive research developed over the years, in industries and by many scientists. Innumerable approaches have successfully been implemented to model this welding technique. Recently, an extensive review conducted by (He et al., 2014) demonstrated the widespread use of numerical analysis for FSW applications, this review presented a comprehensive analysis of approaches that have successfully developed advanced models of the FSW. Scaling models, FE models, grid based methods, Lagrangian particle methods, Discrete Element Method (DEM), meshless methods, CFD, Analysis of Variance (ANOVA), cellular automata, solid mechanics and NN are among the predominant approaches proposed to simulate and assist a better understanding of complex phenomena present in this welding technique.

Due to the plastic deformation of materials and the heat generated during the process, the development of models that can simulate the thermomechanical behaviour of the process and plastic flow of the materials is extremely difficult but, at the same time, the development of these models is crucial to gain further insights into the process. For this reason, several studies have been published in this area.

The previously mentioned review includes a considerable amount of publications based on FE and CFD. These have contributed to the design and simulation of thermomechanical behaviour of FSW. As a result of this exhaustive research work on thermomechanical modelling, several software tools, including, ABAQUS, DEFORM, COMSOL, FLUENT, ANSYS, STAR-CCM+, have been developed to produce advanced models of FSW (He et al., 2014). It is worth noting that all this effort has contributed enormously in the field of FSW. It is also beneficial for companies to have software available that can model the complex behaviour of the FSW. However, one of the major drawbacks of FE, CFD and the software developed based on these techniques, is the computational complexity. Modelling complex algorithms using FE or CFD requires sophisticated hardware, moreover, the amount of time required to simulate a single model is not suitable for real time applications.

The link between the development of sophisticated mathematical models and practical applications for manufacturing processes is crucial. The importance of models that can simulate the FSW has been described. There is, however, a research gap regarding the creation of not only advanced models, but also, time-efficient and transparent models (i.e., models that can be easy to describe and understand, for experts and non-experts). This thesis predominately focuses on these issues by suggesting the use of CI paradigms to develop intelligent models. These models can simulate the FSW process with high accuracy, create advanced models that are simple to describe and more importantly, can interact with users and process experts to communicate the performance of the process. The motivation for suggesting this user-model communication is that, potentially, these models can have the ability to naturally interact with users and provide useful feedback on the process in real-time. There is a lack of research on this topic, but recently, a review on modelling of FSW focused on the optimisation of the models based on CI inspired algorithms has been published (Singhal, Singh, and Raj, 2014). This review highlights the need for the development of algorithms based on CI that can efficiently optimise manufacturing processes. The review is not exhaustive but it does offer a good understanding of state-of-the-art CI-based modelling. The following Section, will describe the fundamental concepts of CI and the main CI-based approaches used in this investigation. A review of research papers that have used these approaches for modelling the FSW will then be presented.

2.3 Data-driven modelling

Data-driven models attempt to describe complex systems without including prior explicit knowledge of their physical behaviour. Another benefit of these modelling techniques is the ability to describe complex systems even with small datasets. These approaches have been developed with the contribution from data mining, pattern recognition, CI, machine learning and other artificial intelligence paradigms. Data-driven modelling approaches are widely used in material science and engineering. The several data-driven modelling methods which have been used in these areas include ANN, Fuzzy Systems, GA, SVM, Gaussian process, and Bayesian, among others (Moraga, 2005; Solomatine et al., 2008).

The benefits of using data-driven modelling based on CI paradigms are: the interpretability of the models, high accuracy and lower computational cost, when comparing with numerical based modelling approaches (FE and CFD). GA are population-based evolutionary systems with the ability to solve single-objective and multi-objective optimisation problems. This thesis takes advantage from the best characteristics of each CI technique to create intelligent hybrid models which can efficiently analyse and predict the performance of complex industrial processes; create new model-based process monitoring methods; and optimise in real-time the process' performance.

2.4 Fundamental concepts of CI

CI is a field of intelligent information processing related with computer science and engineering. As shown in Figure 2.9, the escence of CI involves Fuzzy Systems, NN and Evolutionary Computation, among other techniques (Pedrycz and Gomide, 2007b). As the latter describes, there is a need to develop computational interfaces that are intuitive to humans. This is the fundamental concept of the emerging HCS research, the primary objective is to make computers adjust to people by being more natural and intuitive to use (Pedrycz and Gomide, 2007c). CI paradigms are certainly HCS as they rely on humans to desing and build the systems, and humans benefit from CI systems as they can find optimal solutions. One of the aims of CI is to develop intelligent systems with comparable human performance when processing information, it is therefore important to develop human-machine systems able to colaborate together and take decisions.

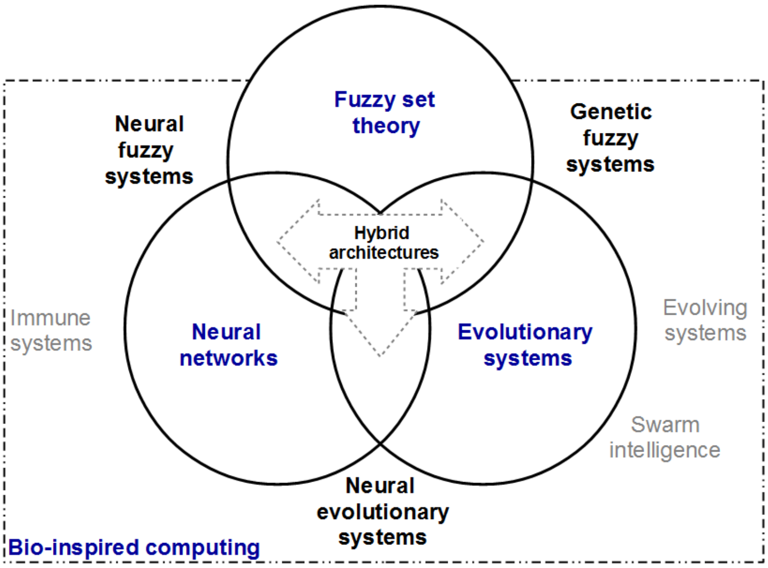

Figure 2.9 CI paradigms (Pedrycz and Gomide, 2007b)

CI paradigms are inspired by biological systems, but none of these mechanisms are superior to any others. Recent trends in research and applications of CI techniques emphasise the development of effective hybrid CI systems. This research focuses on hybrid models based on NN; these approaches are proposed due to their ability in capturing complex patterns that can be found in data from complex systems. NN are routinely combined with Fuzzy Systems and GA to develop human-centered and highly transparent models.

2.4.1 Neural Networks

ANN are computational models of neurons based on how the human brain works. In this context, a neuro is defined as a special biological cell that processes information. The main components of a neural cell are shown in Figure 2.10 where dendrites transmit signals from other neurons into the cell body or soma, possibly multiplying each incoming signal by transferring *weighting coefficient*. In the soma, cell capacitance integrates the signals which are channelled through the axon hillock. Once the composite signal exceeds a cell *threshold*, a signal, is transmitted through the axon. Cell nonlinearities make the composite a *nonlinear function* of the combination of the arriving signals. The synapses operate through the discharge of neurotransmitter chemicals across intercellular gaps and can be either excitatory (tending to fire the next neuron) or inhibitory (tending to prevent firing of the next neuron). A mathematical model of a neuron in Figure 2.11 shows the dendrite weights v_j, the firing threshold v_0 (also referred to as bias), the summation of weighted incoming signals and the nonlinear function $\sigma(.)$ (Lewis, Yesildirak, and Jagannathan, 1998).

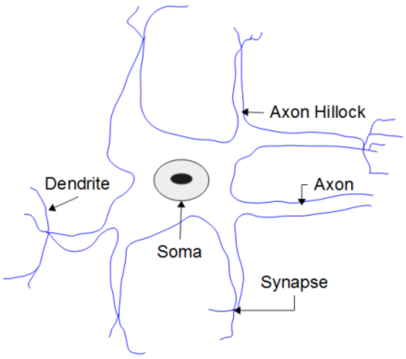

Figure 2.10 Neuron's anatomy

(Engelbrecht, 2007)

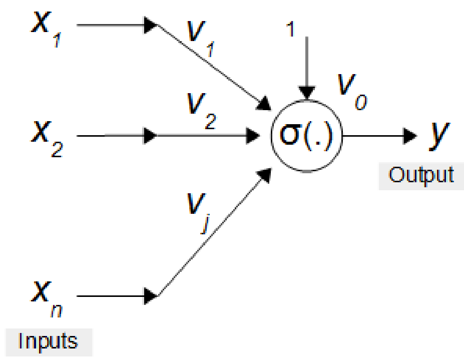

Figure 2.11 Mathematical model of a neuron

Architectures of NN

A NN is a layered network of artificial neurons, which may consist of an input layer, hidden layers and an output layer. Artificial neurons in one layer are connected fully or partially to the artificial neurons in the next layer. Feedback connections to previous layers are also possible. In Figure 2.12 a typical NN structure is illustrated.

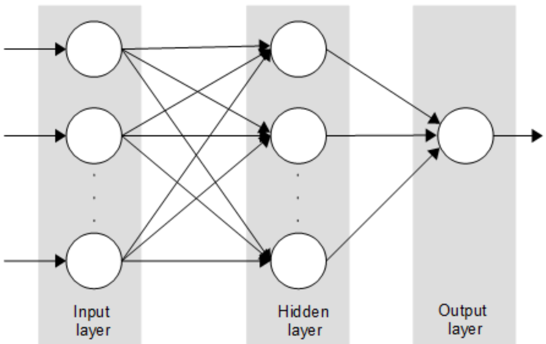

Figure 2.12 The basic structure of neural networks

Due to their efficiency and ability to solve complex problems, NN have been used in a wide range of applications, including, classification, pattern recognition, optimisation, control, time series modelling and data mining (Engelbrecht, 2007). Different types of NN have been developed and can be classified depending on its applications or attributes:

Learning methods	Topology	Connection type	Application
• Supervised • Unsupervised • Reinforcement	• Single layer • Multilayer • Recurrent • Self-organized	• Static (feedforward) • Dynamic (feedback)	• Classification • Clustering • Function approximation • Prediction

Figure 2.13 Classification of NN regarding their applications or attributes

In general, NN are powerful function approximators and clustering devices in which learning procedures provide the key for development (Pedrycz and Gomide, 2007a). The learning process of a NN consist on adjust the weights v_j and threshold v_0 values until a certain criterion is satisfied. Weights and thresholds values are computed so the NN can learn the optimum values from the given data. In supervised learning, the network is provided with a training set, pairs of input and the corresponding output samples. Weights are adjusted in such a way that the network will produce outputs that are as close as possible to the known outputs of the training dataset. Unsupervised learning does not require any outputs associated with the input. This learning method aims to reveal the essential structure in the data. For the reinforcement learning, the network receives only high level guidance. For good performance, the neurons are rewarded but penalised for bad performance. For the models developed in this thesis, the RBF neural networks are proposed, due to their transparency and learning abilities as described in the following Section.

Radial basis function neural networks

RBF neural networks are multidimensional nonlinear function mapping which depend on the distance between the input vector and the center vector. RBF networks have been found to be powerful paradigms for learning complex input-output relationships. An RBF network with an n-dimensional input $x \in \Re^n$ and a single output $y \in \Re$ can be represented as follows (Gupta, Jin, and Homma, 2003b):

$$\boldsymbol{y \triangleq f(x) = \sum_{i=1}^{n} w_i \emptyset_i(\|x - c_i\|)} \qquad (2.1)$$

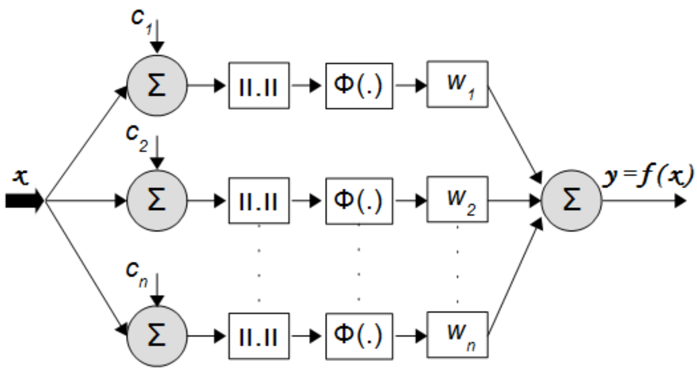

Figure 2.14 Representation of the RBF network

Where $\emptyset_i(\|x - c_i\|)$ is the *radial basis function* of x, $c_i \in \Re^n$ are the centres of the radial basis functions and w_i is a weight parameter. For modelling applications, the radial basis functions most frequently used for this neural network are Gaussian functions:

$$\boldsymbol{\emptyset_i(x) = exp\left(-\frac{\|x - c_i\|^2}{2\sigma_i^2}\right)} \qquad (2.2)$$

Where σ_i is a scalar width parameter for this unit. Using the Gaussian radial function given in Equation 2.2, the output of the RBF network in Equation 2.1 can be rewritten as follows:

$$\boldsymbol{y \triangleq f(x) = \sum_{i=1}^{n} w_i \, exp\left(-\frac{\|x - c_i\|^2}{2\sigma_i^2}\right)} \qquad (2.3)$$

The advantages of RBF networks include the linearity in their parameters and the fast and efficient training methods. Additionally, unlike multilayer perceptrons, RBF networks have a strong theoretical foundation (Kecman, 2001). In modelling, RBF networks have been combined with fuzzy systems and genetic algorithms, to create hybrid models that are computational efficient and transparent (M. Y. Chen and Linkens, 2001; Hong, Oh, Kim, and Lee, 2001; Pedrycz and Gomide, 2007a; Sánchez, Jiménez, Sánchez, and Alcaraz, 2010).

2.4.2 Fuzzy systems

The fuzzy set theory was proposed by Zadeh, he introduced the use of fuzzy sets as *'a class of objects with a continuum of grades of membership'* (LA Zadeh, 1965) p. 338. This theory embraces complex phenomena when *'traditional techniques of system analysis are not well suited for dealing with humanistic systems because the fail to come to grips with the reality of the fuzziness of human thinking an behaviour '* (L. A. Zadeh, 1973) p. 29. Fuzzy Systems have the ability of modelling complex systems via simple structures. Fuzzy Systems are human-centric-based paradigms that describe nonlinear systems by using fuzzy sets, fuzzy rules and linguistic variables. 'Linguistic variables' are variables whose values are not numbers but words or sentences in a natural or artificial language (L.a. Zadeh, 1975).

By definition, fuzzy sets are sets whose elements have degrees of membership (LA Zadeh, 1965) p. 339, and are defined as follows.

> *"Let X, be a space of points (objects), with a generic element of X denoted by x. Thus* $X = \{x\}$*, then, a fuzzy set (class) A in X is characterised by a membership (characteristic) function* $f_A(x)$ *which associates with each point in X a real number in the interval* $[0, 1]$*, with the value of* $f_A(x)$ *at x representing the 'grad of membership' of x in A."*

Fuzzy Systems have n inputs $x_i \in X_i$, where $i = 1, 2, \dots, n$ and X_i is the universe of discourse for x_i, and one output $y \in Y$, where Y is the universe of discourse for y.

Figure 2.15 shows the basic representation of Fuzzy Systems where the fuzzifier converts a set of input data x into fuzzy sets. The inference uses the rules in the rule base to convert these fuzzy sets into other fuzzy sets that are representative of the recommendations of the various rules in the rule base. The defuzzification phase combines these fuzzy recommendations to give an output y. The fuzzy rule base consists of a set of fuzzy IF-THEN rules.

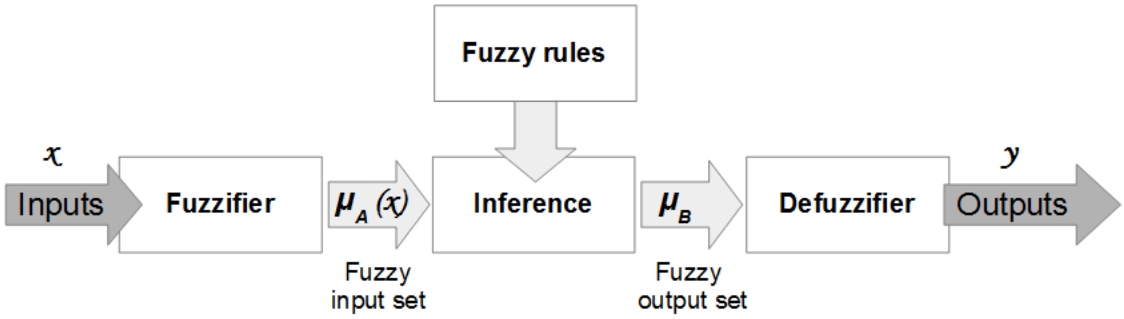

Figure 2.15 A Basic representation of Fuzzy Systems

The fuzzifier is a component that maps the real valued input variable x on to a fuzzy set A, Gussian, trapezoidal and triangular are the types of fuzzifiers frequently used. The defuzzifier is implemented to specify a point y that best represents a fuzzy set B in the output space. The defuzzifier techniques that are frequently proposed are the centre of gravity, centre of area, centre average, and maximum defuzzifier (L.-X. Wang, 1997). The fuzzy rule-base is the core of fuzzy systems: it consists of the fuzzy IF-THEN rules. The most popular methods to express a fuzzy rule are Mamdani-type and Sugeno-type. A Mamdani fuzzy IF-THEN rule is expressed as:

$$Rule^m: IF\ x_1\ is\ A_1^m\ AND\ \dots AND\ x_n\ is\ A_n^m\ THEN\ y^m\ is\ B^m$$

where m is the number of rules, A_n^m and B^m are fuzzy sets in the input space $U_n \subset R$ and $V \subset R$ respectively, $x_n \in U_n$ and $y^m \in V$ are the input and output variables of the fuzzy system.

A Sugeno type IF-THEN rule is described as:

$$Rule^m: IF\ x_1\ is\ A_1^m\ AND\ \dots AND\ x_n\ is\ A_n^m\ THEN\ y^m = g^m(x_1, \dots, x_n)$$

The fuzzy inference engine is a component in which the fuzzy IF-THEN rules are combined in order to build a map from the fuzzy inputs to the output fuzzy set. There are various types of fuzzy inference process and fuzzy operators, a complete description can be found in (L.-X. Wang, 1997).

Fuzzy Logic systems

As previously described, NN have the ability to approximate a function; however, to translate the results in terms of natural language is necessary the use of FL systems. FL is a tool for embedding structured human knowledge into workable algorithms. The main advantage of FL systems, for modelling approaches, is their transparency and interpretability of the models via 'linguistic variables'. FL models extract knowledge from data which can then be presented in human-based reasoning (linguistic IF THEN rules). Many approaches have been developed using FL. They have been successfully applied in real-world systems such as fuzzy washing machines, digital image stabilizer, fuzzy systems in cars, fuzzy control of subway trains (L.-X. Wang, 1997).

Neural-Fuzzy modelling

A variety of hybrid approaches such as Neuro-Fuzzy systems have been proposed to improve the capability of Fuzzy Systems. Neuro-fuzzy systems combine the learning ability from NN with the reasoning ability of Fuzzy Systems. One of the first frameworks based on hybrid systems was introduced by (Jang, 1993), the author developed an Adaptive-Network-based Fuzzy Inference System (ANFIS). The architecture of ANFIS is a combination of NN and Fuzzy Systems that are used to describe the behaviour of complex systems by a set of fuzzy rules. Chen and Linkens proposed a variety of NF frameworks to generate and optimise the parameters of fuzzy models (Linkens and Chen, 1999). They also developed a rule-base self-extraction approach that creates interpretable fuzzy models which are computationally efficient and linguistically interpretable (M.-Y. Chen and Linkens, 2004). The potential of neuro-fuzzy systems for industrial applications was demonstrated by (Abbod, Zhu, Linkens, Sellars, and Mahfouf, 2006; M. Y. Chen and

Linkens, 2001; M.-Y. Chen and Linkens, 2004). The hybrid models proposed were used to predict crucial properties of metals, including, tensile strength, yield stress and elongation, furthermore, the NF-models were able to predict the microstructure of the materials by predicting the grain size. A refined version of NF modelling for industrial applications is presented by (George Panoutsos and Mahfouf, 2010), they combined NF modelling ideas with theory of fuzzy information granulation to capture the system behaviour of complex and imprecise dataset of heat treated steel. The models presented are able to accurately predict steel properties such as tensile strength, elongation and impact energy. The final structure of the models is highly transparent.

2.4.3 Genetic Algorithms

GA are direct, parallel, stochastic methods for global search and optimisation (Sivanandam and Deepa, 2008). GA attempt to computationally mimic the systems based on natural evolution theory as proposed by Charles Darwin, namely: reproduction, natural selection and diversity of the species. GA were first proposed by Holland (Holland, 1975), who described how to apply the principles of natural evolution to optimisation problems. Major contributions in the field were then developed by De Jong (De Jong, 1975) and Goldberg (Goldberg, 1989). They demonstrated the ability of GA to solve and optimise difficult problems, and their contributions lead to successful applications of GAs. (Haupt and Haupt, 2004) presents some of the advantages of these techniques, including the ability of GA to:

i. Optimise with continuous or discrete variables
ii. Simultaneously searches from a wide sampling of the cost surface,
iii. Optimise variables with extremely complex cost surfaces
iv. Provide a list of optimum variables, not just a single solution.

The GA operates on a population of potential solutions applying the principle of survival of the fittest to produce increasingly more precise approximations to a solution. At each generation, a new set of approximations is created by the process of selecting individuals according to their level of fitness, just as in the natural selection concept: '*Preservation of favourable variations and rejection of unfavourable variations*' (Darwin, 1859), p. 81. All the information about the individuals is stored in a chromosome to create populations.

The general algorithm for a GA can be listed as follows:

i. Initial population: generate a set of possible solutions to a given problem.
ii. Survival of the fittest: evaluate each of those solutions, and decide on a fitness level.
iii. Apply selection: from these solutions breed new solutions for the new generation, here, the parent solutions that were more 'fit' are more likely to reproduce, while those that were less 'fit' are more unlikely to do so.
iv. Exhaust search: solutions are evolved over time, by repeating the process each generation.
v. Terminate: when a solution has been found or other termination criteria has been met the algorithm stops.

GA can be defined by either binary or continue values (Haupt and Haupt, 2004). In this investigation, the continuous GA will be applied; the basic structure of GA can be illustrated as follows:

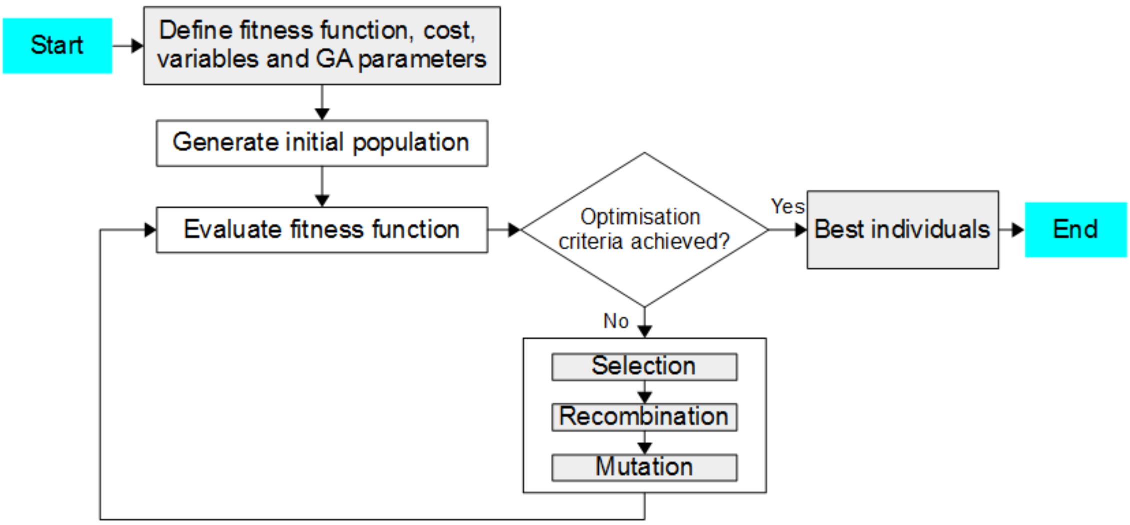

Figure 2.16 Flow chart of a continuous GA

Selection is the process of choosing parents from reproduction; recombination combines the information from two parent chromosomes using an operator. The operator for this recombination process is known as crossover. Its function is to combine the information from two parent chromosomes and create a new chromosome. Mutation is a reproduction operator that randomly alters the values of genes in a parent chromosome (Haupt and Haupt, 2004).

The procedure of a generic GA is given as follows (Goldberg, 1989):

Step 1: set $t = 1$. Randomly generate N solutions to form the first population, P_1. Evaluate the fitness of solutions in P_1.

Step 2: *Crossover*, Generate an offspring population Q_t as follows:

2.1 Choose two solutions x and y from P_t based on the fitness values.

2.2 Using a crossover operator generate offspring and add them to Q_t.

Step 3: *Mutation*, mutate each solution $x \in Q_t$ with a predefined mutation rate.

Step 4: *Fitness assignment*: Evaluate and assign a fitness value to each solution $x \in Q_t$ based on its objective function value and infeasibility.

Step 5: *Selection*: Select N solutions from Q_t based on their fitness and copy them to P_{t+1}.

Step 6: If the stopping criterion is satisfied, terminate the search and return to the current population, else, set $t = t + 1$ got to Step 2.

GA are less likely to become stuck in local minima when compared with back-propagation methods (Larose, 2007; Montana and Davis, 1989). GA are approaches often used to perform optimisation within a NN, as an alternative to the usual back-propagation method. A good example of these applications for analysing complex industrial data is given in (Yang, Linkens, and Mahfouf, 2003). These hybrid models were developed to predict the flow stress behaviour in aluminium. The high accuracy and transparency of the models created was demonstrated via GA-NN. By using GA to optimise the process parameters, the authors showed that the NN structure can be easily simplified. They proposed the use of continuous GA with real-values instead of binary with the aim of reduce computational work.

GA are population-based Evolutionary Systems with the ability to solve single-objective and multi-objective optimisation problems. As most real-world problems are multi-objective (i.e., solutions are in conflict with each other), many engineering problems require minimize costs while maximising performance. The use of multi-objective algorithms is therefore proposed in this investigation. The following Section will review the use of GA for multi-objective optimisation.

Multi-objective optimisation

Multi-objective optimisation involves the minimization or maximization of more than one objective function. The multi-objective optimisation problem may contain a number of constrains which any feasible solution must satisfy (Deb, 2001). The multi-objective optimisation problem for minimization can be defined as:

$$Find\ a\ vector\ x\ \in X, which\ minimizes:$$

$$f(x) = \left(f_1(x),\ \ f_2(x), \dots, f_k(x)\right)^T$$

$$subject\ to \qquad g_1(x)\ \leq 0, \dots, g_m(x)\ \leq 0$$

$$and/or \qquad h_1(x) = 0, \dots, h_n(x) = 0$$

Where X is the feasible space of decision vectors, x is the vector of decision variables and k is the number of objectives. The number of inequalities is m and the number of equality constraints is n. To describe the concept of optimisation for the minimization problem presented above, the definitions of Pareto domination and the Pareto-optimal are introduced (Deb, 2001; Sawaragi, Nakayama, and Tanino, 1985):

Definition Pareto domination

> *One solution $x_1 \in X$ dominates another solution $x_2 \in X$, if $f_i(x_1) \leq f_i(x_2)$, $\forall_i \in k$, and $f_i(x_1) < f_i(x_2)$ for at least one $i \in k$.*

Definition Pareto optimal solutions

> *Also known as non-dominated solutions: One solution $x^* \in X$ is Pareto optimal if for every $x \in X$, $f_i(x) \geq f_i(x^*)$, $\forall_i \in k$.*

The first multi-objective GA, known as VEGA (vector evaluated GA) was proposed by (Schaffer, 1985). Since then, several multi-objective algorithms based on Evolutionary Algorithms have been developed. In (Deb, 2001), Deb presents an exhaustive analysis of the most widely known algorithms. He introduces the background, describes the theory, and analyses the advantages and disadvantages of each algorithm. This Section will review three multi-objectives algorithms: Multi-objective genetic algorithm (MOGA) (C.M. Fonseca and Fleming, 1993b) which were implemented in MATLAB (C.M. Fonseca and Fleming, 1993a), fast Non-dominated Sorting Genetic Algorithm II (NSGA-II) which is one of the most widely used algorithms (Deb, Pratap, Agarwal, and Meyarivan, 2002) and finally, a micro-GA (Coello and Pulido, 2001a) which is proposed as a faster and computationally lower in cost algorithm when compared with NSGA-II.

Multi-objective GA

MOGA was first introduced by (C.M. Fonseca and Fleming, 1993b), the authors were pioneers in developing a GA algorithm for multi-objective problems focused on diversity in the non-dominated solutions. The MOGA assigns the fitness function by Pareto ranking, and the diversity mechanism used is fitness sharing by niching: The fitness Pareto ranking is obtained when, for each chromosome, c_i calculates the number of chromosomes which dominate (n_i). For rank $r_i = 1 + n_i$; the fitness is evaluated to c_i using linear interpolation so that c_i with the lowest rank has the maximum fitness. Once the ranking is performed, a raw fitness to a solution is assigned based on its rank, in order to maintain diversity among the Pareto optimal solutions. The authors introduced niching methods among solutions of each rank. The rest of the algorithm uses a classical GA structure: selection, crossover and mutation. The GA toolbox used in MATLAB was developed based on this algorithm. Additionally, the authors suggest MOGA as a tool for decision making support in the design of engineering and control systems applications (C.M. Fonseca and Fleming, 1993a). Since then, many applications have been developed using this algorithms to solve many challenging real-world optimisation problems (C.M. Fonseca, Fleming, Zitzler, and Deb, 2003).

Non-dominated sorting Genetic Algorithm II

The NSGA-II proposed by (Deb et al., 2002) employs a crowded tournament selection operator which is designed to keep the diversity of the solutions. NSGA-II uses an elitist operator which combines the best parents with the best offspring. The main features of the NSGA-II summarised by (Deb, 2012) are:

i. It uses an elitist principle.
ii. It uses an explicit diversity preserving mechanism.
iii. It emphasizes non-dominated solutions.

A recent survey (A. Mukhopadhyay, Maulik, Bandyopadhyay, and Coello, 2014; Anirban Mukhopadhyay, Maulik, Bandyopadhyay, and Coello, 2014) illustrates the popularity and efficiency of these algorithms. The objective is to solve real-live data mining problems involving multiple conflicting measures of performance.

Micro-GA

The first micro-GA algorithm was implemented by (Krishnakumar, 1989), he used a population size of 5, a crossover rate of 1, a mutation rate of zero and an elitist strategy which copies the best string found in the current population to the next generation, and the selection process was created by declaring as a winner the individual with the highest fitness. The author compared his approach with a classic GA. He reported faster and better results when using a micro-GA for single-objective optimisation. As a result, a micro-GA for multi-objective optimisation was proposed by (Coello and Pulido, 2001a). This algorithm uses two memories: (i) as a source to maintain the diversity and (ii) to achieve members of the Pareto optimal set. The population is operated in a similar way to that of the single-objective micro-GA. The authors compared this micro-GA multi-objective approach with NSGA-II; the multi-objective micro-GA exhibited a low computational cost than NSGA II.

The CI paradigms reviewed in this Section have been applied to many challenging real-world problems. Modelling techniques have been used as tool by industries to improve their manufacturing processes and develop new technologies. The following Section will present literature related with the use of these approaches for FSW.

2.5 Modelling FSW using CI approaches

Over the last two decades, the impact and contribution of FSW for joining technology have been significant for many industries. As a result, considerable efforts have been made to improve this welding technique and its applications, in particular towards process certification. Modelling techniques are proposed as a tool to gain deeper understanding into the complex phenomena involved in this welding process and predict its performance. The use of advanced models has assisted the evaluation of the properties of the welded materials; the reduction of expensive destructive testing, and the deep analysis of the influence of the FSW parameters over the final product. As discussed in Section 2.2, several models based on a variety of advanced mathematical models have been developed. The use of modelling techniques in FSW can also assist in the identification of the optimal POW. This Section, reviews several CI model-based approaches that have been proposed for FSW. The literature presented in this Section is specially focused on the CI paradigms previously introduced in Section 2.4.

Over the last decade, NN have been actively proposed to model this welding process, the NN-based models have successfully been used to predict critical mechanical properties including, UTS, YS and elongation. The research literature presented in this Section reflects the significance that NN have to map complex relationships that can be found during the FSW process. The ability of NN to analyse complex patterns and predict the performance of the process has been demonstrated in various comprehensive studies. For instance, (Okuyucu, Kurt, and Arcaklioglu, 2005), first proposed the use of NN for processing complex data from the FSW. The authors used a feedforward single layer NN and the backpropagation algorithm for the learning process. The NN consists of two inputs which are the traverse and welding speeds, and five outputs to predict different properties of the aluminium plates welded by FSW. The properties predicted are hardness of weld metal, hardness of HAZ, elongation, YS, and tensile strength.

The results presented in the latter study were encouraging. As a consequence, further investigations have taken advantage of the abilities that NN have to map the complex relationships found in FSW. Similarly, (L Fratini and Buffa, 2007) successfully used a NN to predict the final microstructure of aluminium alloys. The authors then presented a more detailed study (Livan Fratini, Buffa, and Palmeri, 2009): in both studies, the authors used a supervised multilayer feedforward NN based on backpropagation. The NN consisted of four inputs representing the values of plastic strain, strain rate, temperature and Zener-Hollomon parameter, and one output which represent the behaviour of average grain size. The dataset was produced after a series of experiments conducted by materials science experts and with information from a finite element model (FEM).

The experiments in (Livan Fratini et al., 2009), revealed the deeper understanding of the nugget, TMAZ and HAZ areas in three different types of welding joints: butt joint, lap joint and T-joint. In both studies, the authors demonstrated the ability of NN to learn complex data and predict, with high accuracy, the final grain size of aluminium alloys (AA6082-T6 and AA2031-T8) welded by FSW. They also used the NN model to simulate the behaviour of grain size influenced by two process parameters: tool rotational speed and traverse speed. The obtained results showed excellent agreement with the experimental data.

An approach using GA to optimise the search for a desired solution was presented in (Tansel, Demetgul, Okuyucu, and Yapici, 2010). The authors propose an a approach which uses the knowledge acquired from the NN in (Okuyucu et al., 2005) to find optimal parameters. The authors propose a GA to minimise or maximise welding speed or traverse speed. The authors used the 'reverse engineer' concept, by giving to the system the desired parameters (hardness of weld metal, hardness of HAZ, elongation, YS, and tensile strength). Their approach estimates the optimal values for welding speed and traverse speed. The approach presented in this study demonstrates the use of NN to learn from data and the potential of GA to optimise multiple FSW parameters. However, as the authors acknowledge, their approach is very time consuming.

A more transparent and faster approach which employs both, multi-objective GA and fuzzy modelling, CI-based techniques is presented by (Zhang, Mahfouf, Panoutsos, Beamish, and Norris, 2011). The models developed in this study, were optimised using NSGA-II. The interpretability of the models was enhanced by applying techniques based on fuzzy systems and the efficiency of the model was also improved by using gradient descendent algorithm. Yield strength, weld quality and average grain size were the outputs predicted using only traverse speed and welding speed as inputs of the system. The results showed excellent agreement with the experimental data. More importantly, the models were presented in a linguistic IF-THEN structure. This study demonstrated the use of fuzzy systems to develop models which are simple and can be translated into human linguistic reasoning.

A different technique to better understand the FSW by using NN was proposed by (DebRoy, De, Bhadeshia, Manvatkar, and Arora, 2012). They used a NN to generate a performance index that can predict the durability of the tool. This study shows that NN can be applied to investigate the FSW from every perspective. Another example is given in (Buffa, Fratini, and Micari, 2012), the authors applied NN to predict microstructure and micro-hardness of titanium alloys joined by using FSW. The inputs of the NN used where plastic strain, strain rate and temperature. In contrast with the studies reviewed so far, this work presents the use of NN to analyse information of a different metal other than aluminium.

So far, the literature presented in this Section has demonstrated the use of CI-based techniques to create advanced models of FSW. The models presented have undoubtedly contributed to a better understanding of certain areas of this welding technique. The models mentioned above produce accurate information of the process and its performance. These approaches, however, are often not suited for on-line applications. Nevertheless, efforts have been made to analyse the FSW process data in real-time. The development of applications that can 'online' evaluate and simulate the behaviour of the FSW is an area which clearly requires further research. Until recently, very little interest has been paid to the development of systems used to monitor the FSW performance in real-time and provide useful information to the user.

It is important to develop advanced models of industrial processes, and extract useful information of the systems. Equally important is that the information extracted can be used as a decision support tool for the final user. Global companies are particularly interested in tools which can reduce costs and at the same time improve their manufacturing process.

As presented in Section 2.1.2, FSW is used in many critical applications, shipbuilding and aerospace sector have developed requirements for quality control of the products welded by FSW (Kallee, 2010), one of the reasons why the development of techniques which can ensure the quality of materials welded by FSW is particularly important. There is a definite lack of literature in this field, especially in relation with CI-based techniques. There are, however, some studies which have attempted to develop online techniques, and these can evaluate the FSW. For example, in (Fleming et al., 2008), statistical analysis approaches were employed to investigate the frequency spectra of forces collected during the FSW process. The aim was to detect certain faults during the welding process.

Another approach analysing data information regarding the forces, for a real-time application, was presented by (Boldsaikhan, Corwin, Logar, and Arbegast, 2011). The authors used a NN to classify the quality of the welds according to the frequency produced by the forces. They analysed the frequency information from the forces, produced during the process, classifying it as 'good weld' or 'bad weld'. The results presented in this study were considerable suited for online applications, because, as the authors reported, the algorithm produces these results in 0.01 second. Most recently, an study based on the analysis of peak temperatures was reported by (Imam, Biswas, and Racherla, 2013). The authors correlated the temperatures in the nugget welding zone and the heat affected zone with the microstructure, hardness, and ductility of the welds. The aim was to find a possible relation of these correlations with weld quality. The results showed that temperatures in the HAZ above 410˚C, and in the weld nugget zone below 350˚C, resulted in a loss of ductility, property which can affect the quality of the joints. Currently, temperatures and forces can be recorded in real-time. This is the reason why the results obtained by these approaches are encouraging. It is worth mentioning that, to date, not studies or literature was found in relation with intelligent control systems that have implemented these techniques. It is also worth mentioning that there is a specific interest from industries and scientists in developing techniques which can offer useful information about the quality of the welds produced during FSW.

2.5.1 Research challenges

In summary, this Section has reviewed interesting approaches that apply numerical analysis and CI-based techniques to create models with the ability to describe complex relationships in FSW. Attempts have been made to extend these approaches for online applications. The motivation to develop advanced methods that not only can predict, but also, monitor the quality of the welds produced by FSW is rapidly growing.

Online monitoring

From the point of view of computational modelling, one of the main challenges is the development of applications which can monitor and evaluate the performance of FSW in real-time. The development of advanced monitoring techniques which can prevent the user of flaws/defect formation is significant for reducing expensive trials which are currently needed to evaluate the mechanical properties, microstructure and quality of the welds. Online monitoring of FSW should be seen as a tool to create defect-free welds without the need for destructive or non-destructive testing evaluations. Another advantage of developing intelligent online monitoring techniques is the prediction of properties of the welds, which can lead to the optimal design of welds.

Automatic detection of abnormal behaviour

As previously explained in Sections 2.1.6 and 2.1.9, the quality of welds produced by FSW is one of the main benefits of this welding technique. As a result, there is considerable interest from industries and FSW technology producers for developing systems that can ensure the quality of the final product. The detection of flaws and defects during the process is a promising area to ensure the quality of the welds. Major efforts, however, are needed to develop intelligent systems which can detect the different flaws found in friction-stir welded products. It has been demonstrated that the quality of the products can be predicted based on the tool rotational speed and traverse speed. Nevertheless, it is essential to apply these prediction models for real-time applications.

Human-centric systems

Despite the drive towards high level of industrial automation (and autonomy) humans still play a critical part in most manufacturing processes. This is predominantly in terms of expert knowledge, which helps optimise processes. It is therefore important maintain the link between human and machines via the development of intelligent techniques and systems that work in collaboration. This collaboration could be in the form of exchanging process information in natural language. The feedback about the system's behaviour should be natural, accurate, and useful for the final user. One of the aims of this concept is to create intelligent models that are transparent to the users and can be used as tools for decision support.

2.6 Summary

In this Chapter, the concept of the FSW process was presented in order to demonstrate the significance of this novel technique for industry, and also to expose the complex phenomena involved in this manufacturing process. FSW has been successfully used to joint materials which are then applied for critical applications. Despite the success of FSW, and the development of innumerable applications, many challenges still lie ahead in order to exploit the potential of this technique, and more importantly, to ensure the quality of the final product. The current literature on processing variables, tool design, and materials was presented with the aim of gaining a deeper understanding of the process. The advantages and disadvantages of this welding technique were also addressed.

The literature revealed that one of the main advantages of this welding technique is the quality of welds. There is thus a specific interest from companies to develop techniques that can provide significant information about the quality and characteristics of the products, without the need of destructive testing techniques. Efforts have been made to develop technologies capable of collecting process information; the most relevant literature on this topic was presented in this Chapter. There is a lack of intelligent systems that can monitor the performance of the FSW process in real-time, and at the same time, detect behaviour which can affect the quality of the final welds. Such systems could have 'intelligent' traits, such as real-time communication to the user, in natural language, of system performance, as well as the provision of possible actions to improve performance.

Evidence presented in this Chapter reveals that one of the main challenges to simulate FSW is the development of models that can describe the complex interactions involved in this process. These include heat generation, material flow, and the influence of welding parameters over the final weld. A brief review of mathematical models which have been proposed to better understand this process was presented in Section 2.2. The review exposed the benefits of using advance modelling techniques to investigate this manufacturing process. Furthermore, the literature revealed that there is gap regarding the developing of more advanced models which can effectively describe the complex interactions of FSW such as material flow, influence of tool design, plastic deformation and heat generation.

The creation of advanced models to simulate complex systems such as FSW is indeed challenging. As explained in this Chapter, one of the main challenges is to develop models which can be both: (i) easy to describe and understand for experts and non-experts, and (ii) suitable for real-time applications. Modelling techniques based on CI have been proposed to address these challenges and are frequently used to analyse and create intelligent models of complex industrial processes. For this reason, this thesis proposes the use of CI paradigms to analyse this manufacturing process. The basic concepts of CI were briefly described in this Chapter. Specific CI paradigms including NN, Fuzzy Systems and GA, which have been successfully applied to create intelligent models of the FSW process, were introduced. Additionally, a survey of CI-based studies that have been proposed to model the FSW process was presented. Finally, particular challenges which were identified during this investigation, related to the development of intelligent models for FSW were discussed. In brief, this Chapter presents a general concept of the FSW process, emphasises the importance of modelling techniques. More importantly, it was identified the lack of intelligent techniques which are unable to effectively monitor the process for real-time applications and at the same time can communicate significant information on the performance of the process.

The next Chapter will present several models which were developed using CI paradigms. The models are able to describe and predict the behaviour of FSW at various and different scales.

3 Multiscale Neural-Fuzzy modelling of complex manufacturing processes for Friction Stir Welding

Overview

Manufacturing processes are often challenging systems to accurately model. This is due to the nonlinearities and complex interactions which are present in the data produced for a single manufacturing routine. The development of approaches that can handle complex data and extract knowledge has been exhaustively studied by many scientists; and one of the innovative approaches proposed is multiscale modelling. This approach is based on the study of sub-processes which are part of a whole system. This concept considers a complex system at various-scales. In this Chapter, multiscale modelling is proposed to create sub-models of complex manufacturing processes such as FSW. The aim of the multiscale concept applied to FSW is to create, for the first time, several sub-models through data-driven modelling to address three different scales: micro-, meso-, and macro-. Each model represents individual behaviour of the whole FSW welding routine. The data-driven models are based on NF modelling which are powerful CI paradigms that can learn from data and more importantly, the models produced are highly transparent: i.e., their interpretability can be translated into human reasoning (IF-THEN rules). The micro-scale model predicts different microstructure properties of the materials, which includes the average grain size and for the first time in this field the cooling rate. The meso-scale includes NF models which predict several mechanical properties: Elongation, ROA, UTS and YS. These mechanical properties characterise some of the mechanical performance of the welded parts. The macro-scale model was developed to predict the overall WQ of the welds produced by FSW.

The Chapter first introduces the multiscale and data-driven modelling concepts. This introduction illustrates the importance of using these techniques for a simulation of complex manufacturing process. Later in the Chapter, the NF modelling methodology is explained in detail. Finally, the multiscale data-driven models based on NF are presented. The models were created using only two process variables, in this case, tool rotational speed and traverse speed. The models were developed using two classification techniques: grid partition and subtractive clustering. The experiments reveal that the use of subtractive clustering reduces the number of rules and the learning ability is superior to grid partition; however, grid partition reduces over-fitting when the models present challenging datasets.

The multiscale models developed in this Chapter are highly transparent. They clearly exhibit the learning and transparency of NF modelling, as the models precisely represent the behaviour of the FSW sub-processes under investigation. Another important contribution in this Chapter is the use of these approaches to demonstrate how the optimal POW of a single material can be clearly identified even at different scales. More importantly, the models predict several mechanical properties and microstructure characteristics of the materials under investigation.

The approach is also able to quantify and predict the quality of the welds, which is one of the main contributions of using these modelling techniques for FSW.

3.1 Multiscale and data-driven neural-fuzzy modelling

Multiscale modelling

Multiscale modelling as a technique for studying complex systems is nowadays of a significant help for engineering and materials science applications. The use of multiscale modelling has become widespread for analysing complex engineering systems (Fish, 2009, 2014; Groen et al., 2014). This technique allows the study of multiple physical processes from a particular system. Multiscale modelling is especially helpful when information is available at different levels of resolution and when embedding a standard problem in a multiscale framework leads to significant computational advantages (Ferreira and Lee, 2007). In (Weinan, 2011), the author explains that computational complexity can be reduced by exploring the disparity between micro and macro-scales of a problem. Multiscale models can capture multiple processes at different scales; each process is presented as a sub-model of the system. Multiscale simulations have been applied to a wide range of engineering problems. As illustrated in (Groen et al., 2014), for engineering and materials science applications, microscopic properties can be of crucial importance for the quality of the overall design of materials. They also explain that materials science applications are naturally multiscale, as the macroscopic properties of many materials are largely characterised through interactions occurring on the microscopic level. Associating the understanding of physical interactions at very small scales with the behaviour at the macro-scales is a major focus in the area of materials science. This discipline has demonstrated that the multiscale modelling and simulation of systems can lead to the development of new technologies (Gates, Odegard, Frankland, and Clancy, 2005).

Chapter 3. *Multiscale Neural-Fuzzy modelling of complex manufacturing processes for Friction Stir Welding*

In general, the aim of multiscale modelling is to address an approach that shares both, the efficiency of macroscopic models, as well as, the accuracy of microscopic models by considering simultaneously models at different scales (Weinan, 2011).

FSW is inherently multiscale, as presented in Chapter 2, the process has been used in critical engineering applications; as a consequence, the multiscale analysis of FSW is important for the identification of defects or flaws. From the point of view of industry, it is particularly important to develop multiscale models of FSW, for example, to evaluate the final mechanical properties and microstructure of welds produced by FSW (Nandan et al., 2008).

In this Chapter, the use of multiscale modelling is proposed to analyse the behaviour of the FSW process at different scales: micro-, meso- and macro-. The aim is to demonstrate the potential of this approach to describe the FSW process from its various sub-systems. The multiscale models will simulate the performance of the process via data-driven approaches (see Figure 3.1 and Figure 3.2).

Data-driven modelling

Data-driven modelling techniques are generally focused on: (i) analysing information that represents the behaviour of complex systems and (ii) determining the relationship between the variables which are involved in the system (input, internal and output variables). Data-driven models attempt to describe complex systems without including prior explicit knowledge of their physical behaviour. Data-driven approaches have been developed with the contribution from data mining, pattern recognition, CI, machine learning and other artificial intelligence paradigms. In industry, the availability of devices which can measure and collect process data, as well as, the use of advanced computational approaches opens up to new scenarios for the development of advanced data-driven models.

In this Chapter, data-driven modelling is suggested as an approach which uses CI paradigms to build models of physical processes. These models can describe the behaviour of physical systems and learn from the system to modify or predict parameters. Figure 3.1 illustrates the general concept of data-driven modelling based on CI. The most widely used methods in CI-based data-driven modelling are NN, GA and Fuzzy Systems. The combination of these methodologies extracts the best characteristics of every approach using them to create powerful hybrid models (Solomatine et al., 2008).

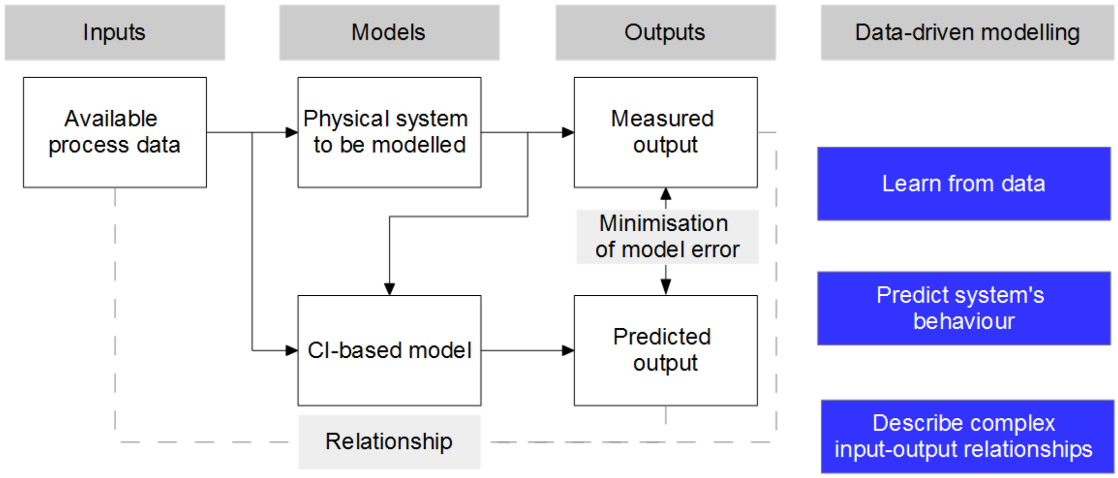

Figure 3.1 General concept of data-driven modelling

As a whole, data-driven modelling techniques are based on the analysis of all the data involved in a system. In this thesis, FSW is the system and the data to analyse was generated using the ARTEMIS tool. Data-driven modelling techniques have been identified as an approach which leads with complex datasets of manufacturing processes such a FSW. The challenge in modelling FSW is the limited experimental data available, it is expensive to create high quality datasets from this process and the analysis of mechanical properties and evaluation of microstructure is also expensive and time consuming.

In the following Sections, several multiscale models of the FSW which were developed using data-driven and NF modelling approaches are presented. Additionally, the use of fuzzy rule-based systems to build transparent models of this complex welding technique is demonstrated.

Process Operating Window

In this Chapter, multiscale and data-driven approaches are presented as techniques to analyse and simulate complex industrial processes. By using these techniques, a better understanding of complex interactions present in physical systems can be achieved. As a result, the regions where the system performs the better can be identified therefore used to optimise the system's performance. For FSW, the identification of optimal POW is crucial, especially to obtain defect-free welds, and to achieve the desired mechanical properties of the materials welded. Currently, most of the POW's for FSW are defined by trial and error methods. These methods are usually expensive and time consuming; the development of computational models allows the process user to easy identify the optimal POW's and minimise the need of trial and error methods. The multiscale models developed in this Chapter, are highly transparent. They clearly exhibit and easily represent the behaviour of the FSW sub-processes under investigation. Furthermore, it is demonstrated how the optimal POW of a single material can be create at different scales.

3.2 A multiscale approach for developing CI-based data-driven models of FSW

As previously introduced, industrial processes are often very difficult to model, mainly, due to the complex behaviour of their variables. As presented in Chapter 2, FSW is a welding technique which is stable along the welding process, with a few independent variables to control. The plastic flow of the materials and thermomechanical behaviour are, however, complex phenomena to understand. As discussed in the literature review, Section 2.1.7, several studies have demonstrated that the material flow behaviour, which is influenced for the process variables, reflects its influence in the generation of defects that can be found in welds produced by FSW (Beamish and Russell, 2010a, 2010b; Nandan et al., 2008).

The aim of the simulations presented in this Chapter is to enhance the fundamental understanding of the FSW process by developing multiscale models using data-driven modelling techniques. These models represent the FSW at various scales. More importantly, the multiscale models assist the process experts to better comprehend and easily identify the POW's of the material under investigation. As illustrated in Figure 3.2, the performance of FSW is assessed in three different scales:

i. **Meso-scale**: Models 1, 2, 3 and 4 describe the behaviour of several mechanical properties: Elongation, ROA, UTS and YS.

ii. **Micro-scale**: Models 5 and 6 simulate the behaviour of average grain size and cooling rate, properties which are strongly related to the final microstructure of the materials (Nandan et al., 2008).

iii. **Macro-scale**: Model 7 represents the behaviour of the quality of welds produced by FSW.

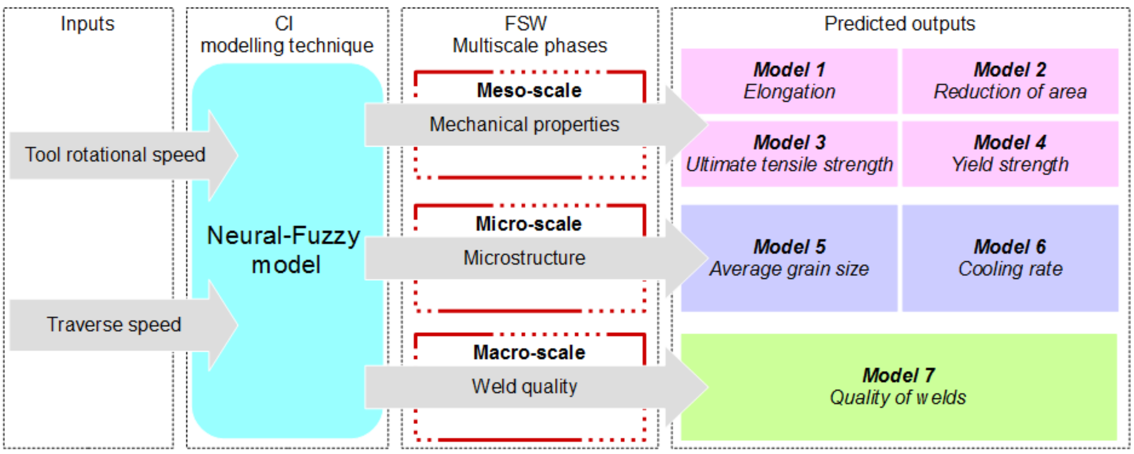

Figure 3.2 A data-driven structure proposed to simulate the multiscale behaviour of FSW

3.3 Experimental data

The dataset, shown in Table 3.1 includes the mechanical properties and microstructure of the welds. This dataset was obtained from welds samples produced by FSW of 6mm thick sheets of aluminium alloy AA5083. The welds were performed using the Tri-flute™ MX tool. The dataset shown in Table 3.2, which represents the cooling rate, was estimated from thermal measurements of weld samples produced with 6mm thick sheets of aluminium alloy AA5083 using the Tri-flat™ MX tool.

Table 3.1 AA5083 dataset using the Tri-flute™ MX tool

Weld sample	Tool rotational speed (RPM)	Traverse speed (mm/min)	Elongation (%)	ROA: Reduction of Area (%)	UTS: Ultimate Tensile Strength (MPa)	Yield strength (MPa)	Average grain size (μm)	Weld quality (0-12)
C11	280	168	19.9029	33.9460	314.7806	171.8666	11.9639	0
C12	280	224	21.4184	31.8447	314.0579	173.0938	-	0
C13	280	280	20.1078	32.9301	314.5284	173.0029	8.8966	0
C14	280	336	20.7682	30.9170	314.2965	176.6526	8.6111	0
C15	280	392	18.6968	29.8833	314.9759	184.0504	6.9829	2
C16	355	213	21.1851	28.2068	313.5182	171.4650	11.7667	1
C17	355	284	18.5264	28.4004	310.5434	172.5717	11.9665	0
C18	355	355	21.7179	32.6291	312.6803	173.9246	10.7214	0
C19	355	426	21.5080	30.7075	312.5699	174.7096	9.7164	0
C20	355	497	20.0090	29.3227	310.6121	173.4202	-	1
C21	430	258	21.3005	-	300.2489	163.3000	14.5185	0
C22	430	344	25.3713	-	295.9089	169.9000	-	0
C23	430	430	17.9744	-	266.3400	162.8000	-	0
C24	430	516	19.6417	-	281.3056	163.6000	10.7752	1
C25	430	602	19.1110	-	296.1344	169.0000	-	1
C26	505	303	18.8152	27.2983	315.2544	173.8484	12.8799	0
C27	505	404	19.6443	27.2994	305.9747	173.5826	-	0
C28	505	505	13.4041	20.3864	275.7257	174.9407	-	1
C29	505	606	21.1323	33.3349	320.1107	177.3667	13.0866	0
C30	505	707	20.7148	30.9903	315.9479	177.8281	11.2733	2
C31	580	348	20.0604	30.3553	315.2621	173.6538	12.2854	2
C32	580	464	12.1529	13.6552	229.0648	175.7041	-	2
C33	580	580	14.9365	18.0198	292.1812	175.8759	-	1
C34	580	696	10.7151	15.1141	263.5498	177.7214	-	5
C35	580	812	9.8258	13.0070	258.1556	176.5837	9.3194	8

Table 3.2 AA5083 thermal dataset using the Tri-flat™ MX tool

Weld sample	Tool rotational speed (RPM)	Traverse speed (mm/min)	Average cooling rate (°C/s)
AW01	400	400	13.8
AW02	500	500	20.5
AW03	600	600	40.8
AW04	700	700	71.1
AW05	400	480	18.9
AW06	500	600	87.9
AW07	600	720	91.6
AW08	700	800	129.8
AW09	400	560	63.3
AW10	500	700	103.5
AW11	600	840	93.9
AW12	400	640	66.5
AW13	500	800	84.2
AW14	600	960	130
AW16	300	300	13.1
AW17	300	360	23.3
AW18	300	420	30.7
AW19	300	480	35.2

As previously noted, a significant challenge for the modelling of FSW is the limited experimental data available. It is expensive to create dataset of welds to obtain a high quality dataset, and furthermore the analysis of mechanical properties and microstructure of the samples is also expensive and time consuming. Therefore, the available datasets are not in the hundreds or thousands of samples as in some other manufacturing processes.

From Table 3.1, the mechanical properties and microstructure measurements were calculated by metallurgical analysis, and the quality index was developed by process experts from TWI Ltd. The cooling rate given in Table 3.2 was calculated from mathematical definitions proposed on previous investigations of cooling rates for aluminium alloys Equation 3.2, (Dobrzański, Król, and Tański, 2010). In the following Section, the fundamental concepts of mechanical properties and microstructure are briefly explained as well as the acquisition process of the datasets. The intention is to illustrate the multiscale behaviour of FSW, which is evident when each concept is individually analysed. This multiscale analysis exhibits how a specific concept can affect the overall quality of the final product.

3.3.1 Mechanical properties

The mechanical properties of materials will describe how the material reacts to external physical forces. These characteristics occur as a result of the physical properties inherent to each material, and are estimated through a series of mechanical tests (Bhadeshia and Honeycombe, 2006; Nandan et al., 2008). A brief description of the mechanical properties which were evaluated to obtain the datasets used for the NF models presented in this Chapter is given below (Mathers, 2014).

i. UTS is the maximum load that the material can withstand while being stretched before breaking.
ii. YS is the point at which the material begins to deform plastically, i.e. when the material changes from elastic to plastic behaviour (permanent deformation).
iii. Percentage of elongation represents how much a material stretches, before reaching it ultimate strength point.
iv. Percentage of ROA is how much a test specimen has necked or reduced in diameter at the point of failure.

UTS and YS are measurements related to the strength of the material, whereas, elongation and ROA indicate the deformational characteristics of the material in relation to applied forces.

To generate the dataset showed in Table 3.1, all the weld samples were tested at room temperature and a two-dimensional digital image correlation system was used for data acquisition and displacement measurements. For each sample, five specimens were produced and tested. The tensile specimens were machined from the nugget zone in transverse orientation to the weld. The strength obtained in this area represents the weakest region of the weld.

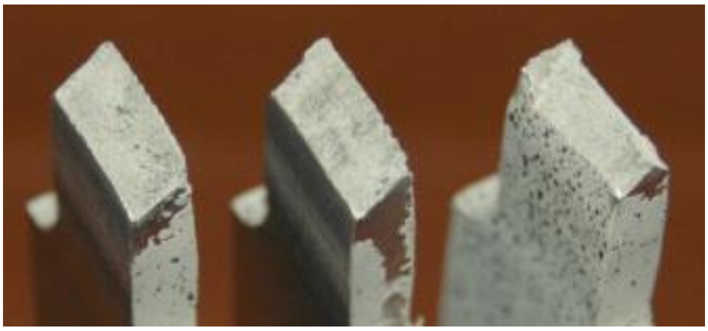

Figure 3.3 The fracture surface of tensile specimens in the HAZ zone (Zhang et al., 2011)

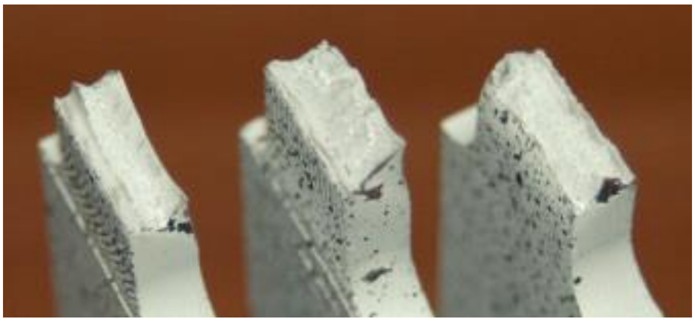

Figure 3.4 The fracture surface of tensile specimens in the nugget zone (Zhang et al., 2011)

According to Zhang in Figure 3.3 and Figure 3.4 (Zhang et al., 2011), failures mainly occurred in the HAZ zone due that this zone has the lowest strength (Mishra and Ma, 2005). The welds with defects, failures may also occur in the nugget zone, where porosity voids are produced.

3.3.2 Microstructure

Average grain size and cooling rate

The microstructure of a material is strongly related to its physical properties, such as: strength, toughness, ductility, hardness, corrosion, resistance, among others (Bhadeshia and Honeycombe, 2006; Nandan et al., 2008). The analysis of grain size of materials that have been thermomechanically affected is often used to evaluate the strength of materials. Grain size is partially influenced by the rate of cooling from the manufacturing process; Figure 3.5 illustrates an example of the microstructure from the centre of the weld zone of a sample welded by FSW. For the case of FSW, the cooling rate represents the change of temperature of the material from semisolid phase to solid phase.

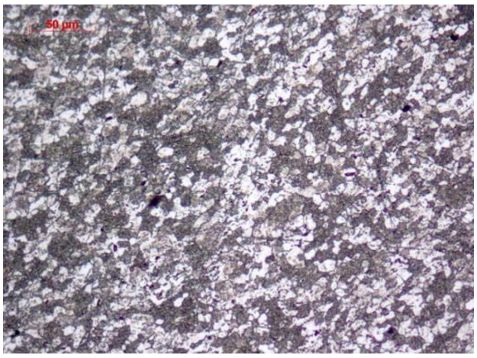

Figure 3.5 Microstructure sample from centre of the weld zone (Zhang et al., 2011)

Insights into cooling rate

In this Section, the use of a thermal imaging camera is proposed as an approach to estimate and potentially monitor the cooling rate behaviour during the FSW process. The average cooling rate measurements given in Table 3.2 were calculated from thermal information acquired during the performance of several weld trials. The information of each weld trial was recorded with a thermal imaging camera which captures sequences of temperatures generated during the welding process. The sequences of each weld sample were then analysed for the first 25 seconds of the welding routine. From this analysis, as shown in Figure 3.6, seven points were monitored to calculate the cooling rate of the material during the process: $Sp1, \dots, Sp7$.

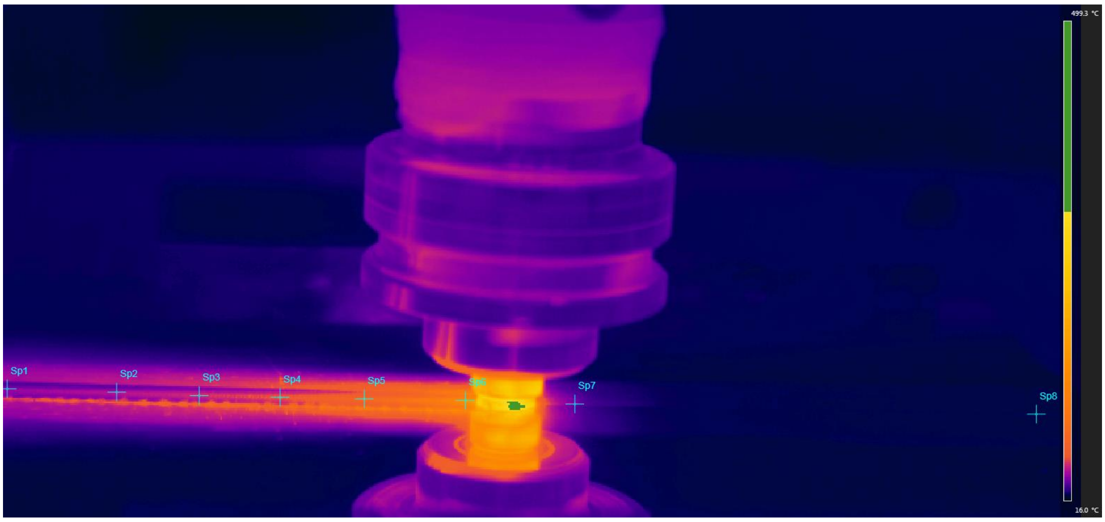

Figure 3.6 Thermal image of weld sample AW08, material AA5083, using the Tri-flat™ MX tool at 700 RPM and 800 mm/min

The behaviour of the analysed points is shown in Figure 3.7; this plot illustrates the cooling rate profiles of a weld sample, in this case AW08. The cooling rate of each profile was calculated using Equation 3.1 (Dobrzański et al., 2010).

$$\boldsymbol{CR_{Sp} = \frac{T_1 - T_2}{t_2 - t_1} \quad \left[\frac{°C}{s}\right]} \qquad \textbf{(3.1)}$$

Were CR_{Sp} is the cooling rate of each profile, T_1 is the maximum temperature that the profile reached and t_1 is the time at that point. The temperature where the profile behaviour establishes i.e., the temperature continuously decreases, is given by T_2 , and t_2 is the time at this point.

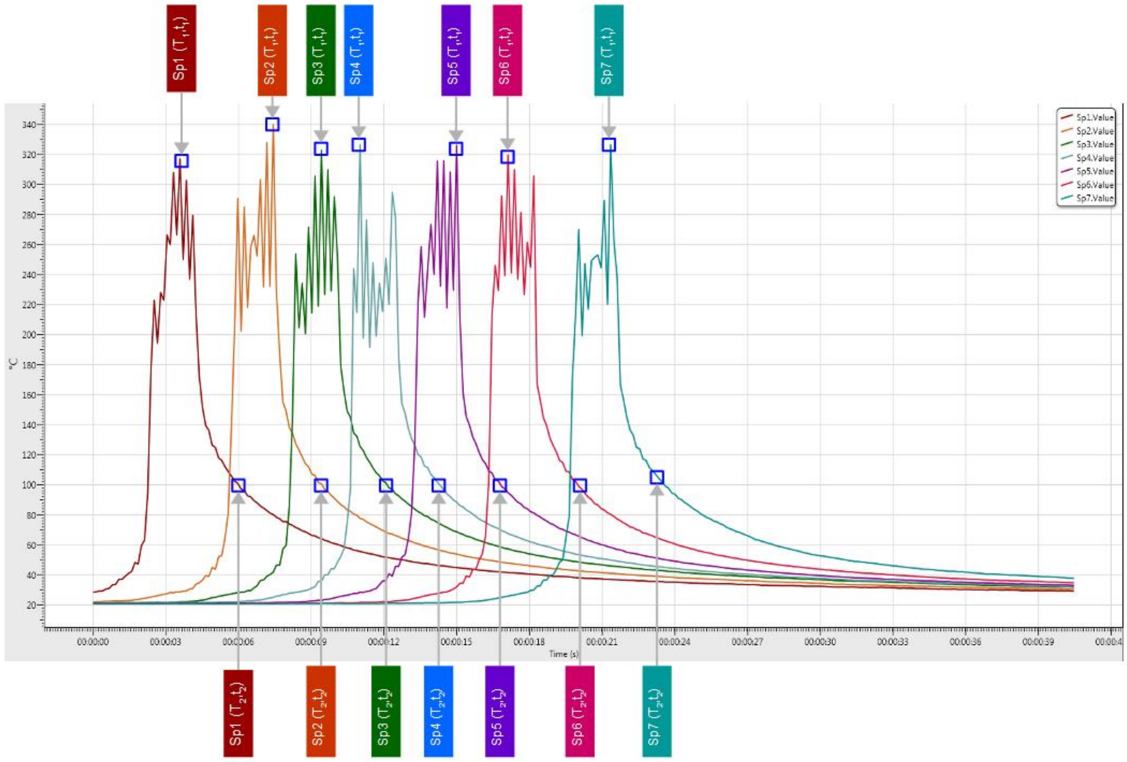

Figure 3.7 Cooling rate profiles extracted from weld sample AW08, material AA5083, using the Tri-flat™ MX tool at 700 RPM and 800 mm/min

The final cooling rate for each weld sample ($CR_{average}$) was then estimated using Equation 3.2.

$$\boldsymbol{CR_{average} = \sum CR_{Sp}} \qquad \textbf{(3.2)}$$

3.3.3 Weld quality index

The quality of the welded samples was quantified by process experts from TWI, Ltd., via four different indices:

i. Bend test-root
ii. Bend test-face
iii. Surface finish
iv. Cross sectional inspection

Figure 3.8 Bend test surface finish and cross-sectional inspection to assess the quality of the joints produced by FSW

Each index is expressed in numerical values between [0 – 3] using expert knowledge, where 0 = none observed flaws. A final index is then constructed by aggregating the four sub-indices. This final index measures the overall 'Weld Quality' (WQ) of the welds, it ranges between 0 – 12, where 0 = 'Good weld quality' and 12 = 'Poor weld quality'.

3.4 Modelling methodology

To create the NF models, the experimental data was divided into two datasets: (i) used for training and (ii) used for testing. As can be observed in Table 3.1, the data samples are scarce and in some cases the data is null. This is thus a challenging dataset to develop models using data-driven techniques due to the lack of information, which can lead to an over-fitting, inaccurate model. To prevent this phenomenon, a cross-validation approach was employed. *Leave 'x' out* cross-validation is a statistical method for evaluating and comparing learning algorithms by dividing all available data into subsets (Jerome, Hastie, and Tibshirani, 2001). For the datasets presented in Table 3.1 and Table 3.2, the process of 'leave X out' cross-validation was applied to establish the best model training regime. The 'leave 5 out' cross-validation was employed for the cases where 25 data samples were available: elongation, YS, cooling rate and weld quality. For the cases where 20 data samples or less were available: ROA, UTS and grain size, the 'Leave 4 out' cross-validation was applied.

In this Section, an NF modelling approach is used based on an ANFIS. This approach is proposed to capture multiscale behaviour of the FSW process in order to map the nonlinear relationships between the process data and the FSW sub-processes. For the learning routine, ANFIS applies a hybrid optimisation method based on back propagation and least square error (Jang, 1993). To validate the accuracy of the models, each sub-process was developed using two classification methods: grid partition and subtractive clustering. The grid-partitioning method defines a number of fuzzy sets for each variable: these fuzzy sets are shared in all the fuzzy rules generated. One of the issues related with the grid partition method is the generation of high-dimensional problems, due to the large number of fuzzy rules generated. On the contrary, with subtractive clustering, the fuzzy sets are generated using clustering techniques. The fuzzy sets are not shared by all the rules as each fuzzy rule is associated to one cluster. This leads to a reduction of rules generation, resulting in a simplified model.

To measure the accuracy of the predicted models, the Root Mean Square Error (RMSE) was employed. This error is frequently used to measure the difference between values predicted by a model and the values actually observed from the environment that is being modelled. The RMSE of a model prediction with respect to the estimated variable X_{model} of a sample of n measurements is defined as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs} - X_{model})^2}{n}} \qquad (3.3)$$

Where X_{obs} are the measured values and X_{model} are the predicted values.

For the datasets used in this Chapter, the RMSE measurements revealed that the models developed using subtractive clustering were more precise in respect to the real data samples, however, when the dataset is more complex, the grid partition models showed a better performance.

The several data-driven models of the sub-processes which represent the multiscale behaviour of the FSW were generated as follows:

i. Dividing the experimental data into subsets via cross-validation approach
ii. Classifying the data using both grid partition and subtractive clustering methodologies
iii. Generation of the model structure and fuzzy-rules using NF modelling
iv. Evaluation of the NF models calculating the RMSE

3.5 Simulation results

As presented earlier and illustrated in Figure 3.2, for each NF model, two inputs were used: tool rotational and traverse speed, seven outputs were evaluated. The simulation response of the seven multiscale data-driven models created is shown in the following Section. The training and testing routines were based on (objective function) the RMSE which represents the performance of the developed NF models. Specifically, the testing performance is used as a measure of model generalisation. The behaviour of the models presented in 3D plots shows the output behaviour as a function of the inputs. Due to the limited datasets used to produce these models, the models appear to extrapolate in regions where there is not enough knowledge (not enough data). Despite this, it is demonstrated that the

NF models reasonably represent the FSW process and predict its complex behaviour in a way that agrees with expert knowledge.

3.5.1 Multiscale models to simulate the performance of mechanical properties in FSW

Model 1: elongation

For model 1, 20 data samples were used for training and 5 for testing (Table 9.4, appendix 2). Figure 3.9 shows the high accuracy of the model developed to predict this mechanical property. In Figure 3.10, the fuzzy-rules generated to predict the elongation of the FSW process are presented. Table 3.3 summarises the model's performance of elongation

Table 3.3 Elongation model's performance

	Fuzzy rules	RMSE of training	RMSE of testing
Grid partition	9	1.8029	2.8276
Subtractive clustering	7	0.0608	4.6683

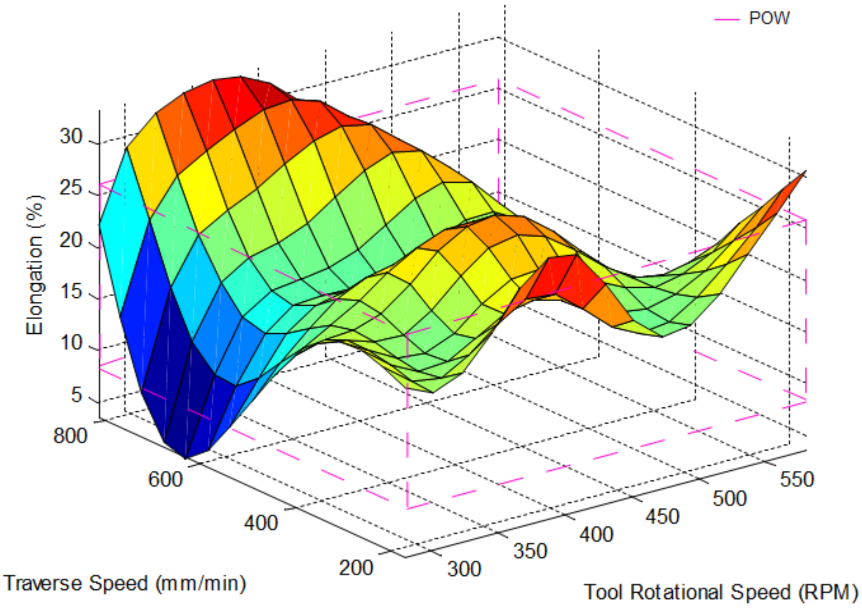

Figure 3.9 The NF sub-process model developed via subtractive clustering to simulate the behaviour of elongation during the FSW process

The NF model created was compared with work that evaluates the process conditions (speeds) with mechanical characteristics such as % elongation. The behaviour of this model shows good agreement with the % elongation behaviour presented in (Han et al., 2009) for the same material AA5083 . The authors report that for RPM speeds around 500 r/min and traverse speeds between 267 mm/min and 342 mm/min, the % of elongation is measured between 10-15 % which is close to the predictions of the NF model presented. As the process conditions and tools are not exactly the same, the accuracy is not exactly the same but it is helpful as a reference and to prove the ability of the NF to predict the elongation for aluminium alloys AA5083. The NF model in Figure 3.9 shows that for values of % elongation > 26 and < 9, (which are values that the model has not learnt before) the process parameters are out of the POW. The linguistic interpretation of the NF model is illustrated the figure below.

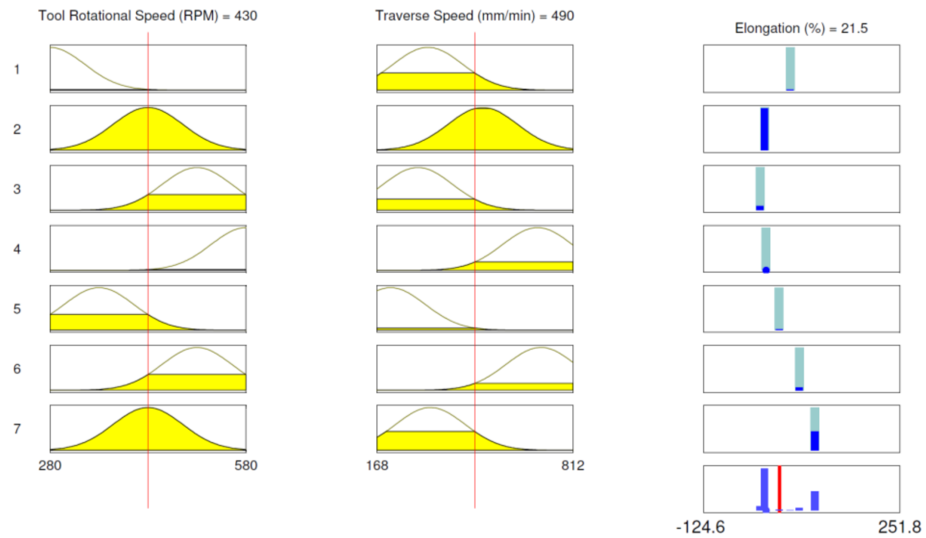

Figure 3.10 Fuzzy-rules and aggregation process created using subtractive clustering techniques to described the behaviour of elongation during the FSW process

In general, there are two principal ways of computing the contribution of each activated rule by using either an *individual rule-based* or a *composition-based inference engine*. The first step of individual rule-based inference is described in Figure 3.10. For each activated rule, the membership function of the IF part of the rule is calculate, and then, the influence on the THEN part of the rule. When this procedure is carried out for all activated fuzzy rules, a process called *aggregation* concludes individual rule-based inference with one output fuzzy set, which is then used for the computation of the output value (Kovacic and Bogdan, 2010). Aggregation is the process where the outputs of each rule are combined into a single fuzzy set. The input of the aggregation process is the list of the truncated output functions returned by the implication process for each rule. The output of the aggregation process is one fuzzy set for each output variable, here, all fuzzy sets assigned to each output variable are combined together to form a single fuzzy set for each output variable using a fuzzy aggregation operator as illustrated in Figure 3.10, Figure 3.12, Figure 3.14, Figure 3.16, Figure 3.18, Figure 3.24 and Figure 3.26.

An example of the linguistic understanding of the fuzzy-rules presented in Figure 3.10 can be interpreted as follows:

1. If **Tool rotational speed** is “low” and **Traverse speed** is “medium-low” then **% elongation** is “medium-high” (elongation values predicted are slightly > 21.5%)
2. If **Tool rotational speed** is “high” and **Traverse speed** is “high” then **% elongation** is “medium-low” (elongation values predicted slightly < 21.5%)
3. If **Tool rotational speed** is “medium-high” and **Traverse speed** is “medium-low” then **% elongation** is “medium-low” (elongation values predicted slightly < 21.5%)
4. If **Tool rotational speed** is “low-high” and **Traverse speed** is “medium-high” then **% elongation** is “medium-low” (elongation values predicted slightly < 21.5%)

5. If **Tool rotational speed** is “medium-low” and **Traverse speed** is “low” then **% elongation** is “medium” (elongation values predicted = 21.5%)
6. If **Tool rotational speed** is “medium-high” and **Traverse speed** is “low-high” then **% elongation** is “medium-high” (elongation values predicted slightly < 21.5%)
7. If **Tool rotational speed** is “high” and **Traverse speed** is “medium-low” then **% elongation** is “high” (elongation values predicted > 25%)

This is a clear example of the interpretability of the models created using NF modelling approaches. The model shows how the linguistic output-performance can be directly used by the process experts.

Model 2: reduction of area

For Model 2, 16 data samples were used for training and 4 for testing (Table 9.5, appendix 2). Figure 3.11 shows the high accuracy of the model developed to predict ROA. In Figure 3.12, the 9 fuzzy-rules generated to predict this mechanical property for FSW can be observed. Table 3.4 summarises the performance of this model. The ROA is an important requirement to ensure the mechanical properties of the materials welded by FSW. For this reason, this investigation project presents a NF model which can be used to predict this property.

Table 3.4 Reduction of area model's performance

	Fuzzy rules	RMSE of training	RMSE of testing
Grid partition	9	1.6500	5.0381
Subtractive clustering	6	0.2372	13.5468

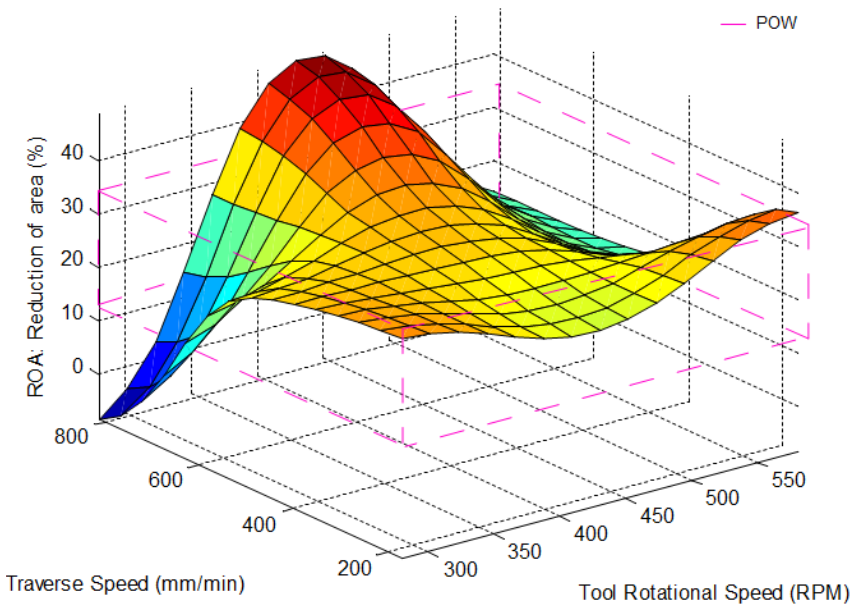

Figure 3.11 The NF sub-process model developed via grid partition to simulate the behaviour of ROA during the FSW process

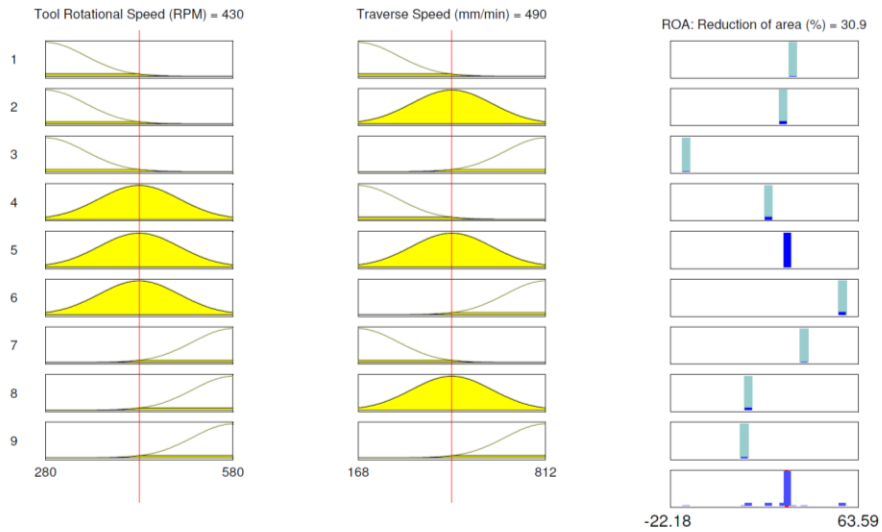

Figure 3.12 Fuzzy-rules and aggregation process created using grid partition techniques to described the behaviour of ROA during the FSW process

1. If **Tool rotational speed** is "low" and **Traverse speed** is "low", then ROA is "medium-high" (% ROA predicted slightly > 30.9)
2. If **Tool rotational speed** is "low" and **Traverse speed** is "high", then ROA is "medium" (% ROA predicted slightly < 30.9)
3. If **Tool rotational speed** is "low" and **Traverse speed** is "low-high", then ROA is "very-low" (% ROA predicted = fail weld)
4. If **Tool rotational speed** is "high" and **Traverse speed** is "low", then ROA is "low" (% ROA predicted slightly < 30.9)
5. If **Tool rotational speed** is "high" and **Traverse speed** is "high", then ROA is "medium" (% ROA predicted = 30.9)
6. If **Tool rotational speed** is "high" and **Traverse speed** is "low-high", then ROA is "very-high" (% ROA predicted > 30.9)
7. If **Tool rotational speed** is "low-high" and **Traverse speed** is "low", then ROA is "medium-high" (% ROA predicted slightly > 30.9)
8. If **Tool rotational speed** is "low-high" and **Traverse speed** is "high", then ROA is "low" (% ROA predicted < 30.9)
9. If **Tool rotational speed** is "low-high" and **Traverse speed** is "low-high", then ROA is "low" (% ROA predicted slightly < 30.9)

Model 3: ultimate tensile strength

For Model 3, 20 data samples were used for training and 5 for testing (Table 9.6, appendix 2). Figure 3.13 shows the high accuracy of the model developed to predict this mechanical property. In Figure 3.14, the 9 fuzzy-rules generated to predict the UTS of the FSW process can be observed. Table 3.5 summarises the performance of this model.

Table 3.5 Ultimate tensile strength model's performance

	Fuzzy rules	RMSE of training	RMSE of testing
Grid partition	9	13.6031	19.0387
Subtractive clustering	7	1.1466	94.2895

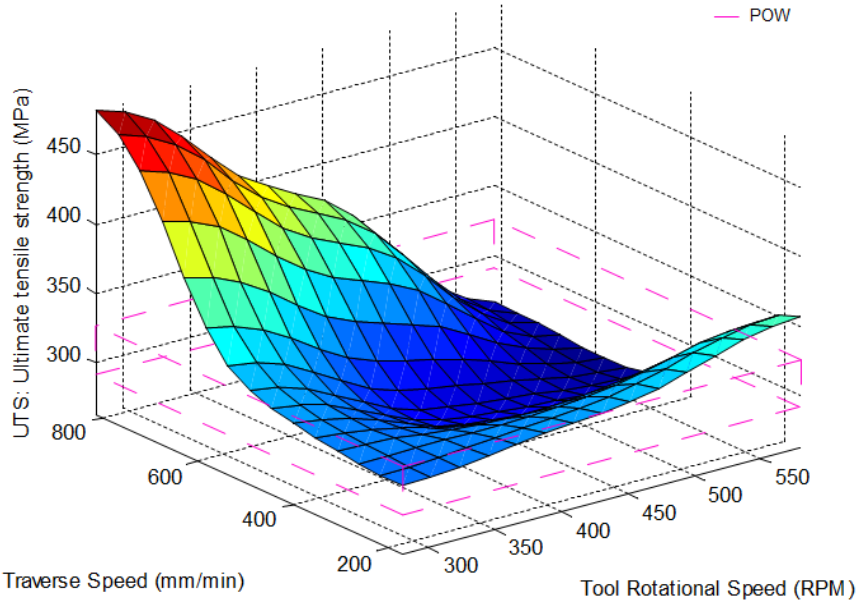

Figure 3.13 The NF sub-process model developed via grid partition to simulate the behaviour of UTS during the FSW process

The created NF model to predict the UTS can be compared with the results reported in (Mourad, Allam, and El Domiaty, 2014), where the mechanical behaviour of friction stir-welded aluminium alloys is studied, this work reports that higher rotational speeds leads to better properties of the weld joint, but by increasing the traverse speed up to a certain speed, the properties start to degrade and inverse effects on the properties take place.

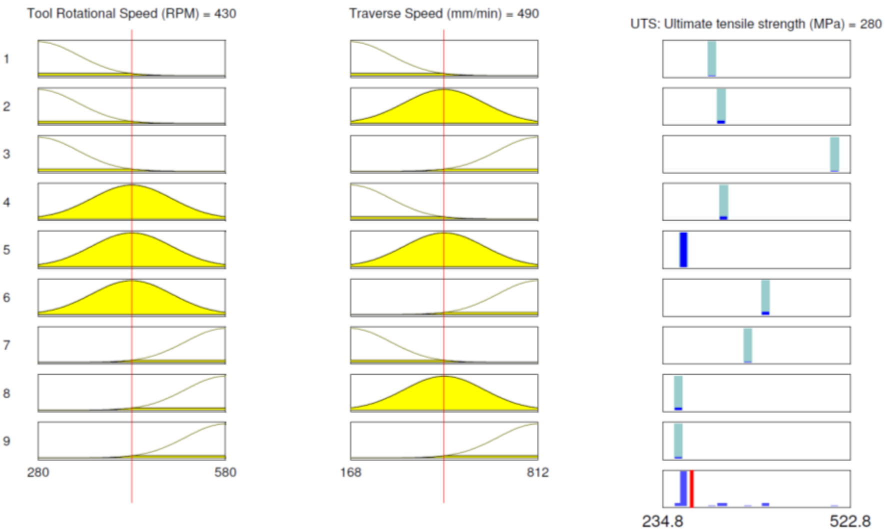

Figure 3.14 Fuzzy-rules and aggregation process created using grid partition techniques to described the behaviour of UTS during the FSW process

Model 4: yield strength

For model 4, 20 data samples were used for training and 5 for testing (Table 9.7, appendix 2). Figure 3.15 shows the good accuracy of the model developed to predict the yield strength. In Figure 3.16 the 7 fuzzy-rules generated to predict the mechanical properties of the FSW process in this case yield strength are presented. Table 3.6 summarises the performance of this model.

Table 3.6 Yield strength model's performance

	Fuzzy rules	RMSE of training	RMSE of testing
Grid partition	9	2.0788	2.6862
Subtractive clustering	7	0.0023	1.9643

The relation of speeds and tensile strength has been studied before using NN, in (Elangovan et al., 2009), the tensile strength is predicted for aluminium alloys AA6061. The tensile strength was assessed using different probe profiles, and various tool rotational speeds between 800-1600 RPM. The research work reported the use of NN to accurately predict this mechanical property.

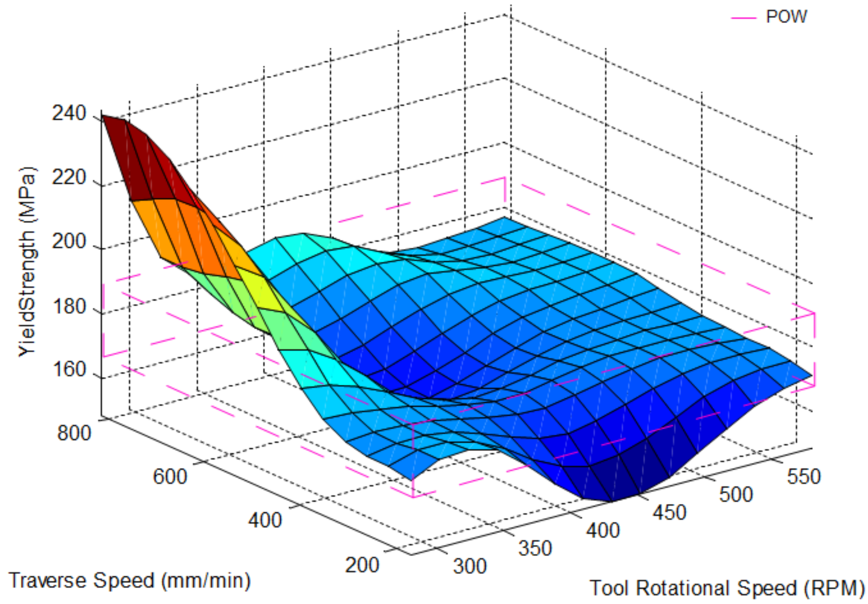

Figure 3.15 The NF sub-process model developed via subtractive clustering to simulate the behaviour of YS during the FSW process

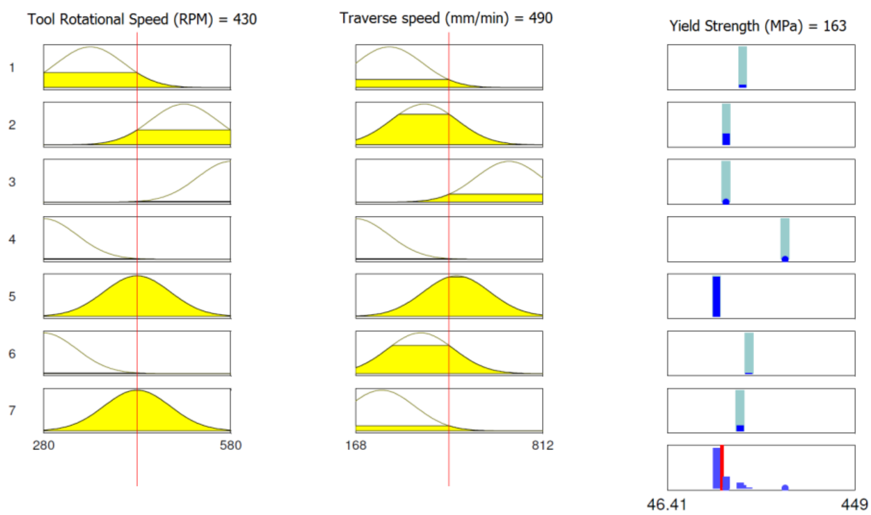

Figure 3.16 Fuzzy-rules and aggregation process created using subtractive clustering techniques to described the behaviour of YS during the FSW process

Similar results were reported by (Zhang et al., 2011), where the prediction of the optimal yield strength was reported to be between 170-185 MPa, which is comparable with the NF model presented in Figure 3.15 which also predicts YS.

3.5.2 Multiscale models to simulate the performance of microstructure in FSW

Model 5: average grain size

In Model 5, 10 data samples were used for training and 5 for testing (Table 9.8, appendix 2); Figure 3.17 shows a good prediction of the model developed to predict the average grain size. In Figure 3.18, the 9 fuzzy-rules generated to predict the average grain size of the FSW process are presented. Table 3.7 summarises the performance of this model.

Table 3.7 Average grain size model's performance

	Fuzzy rules	RMSE of training	RMSE of testing
Grid partition	9	0.0002	2.4401
Subtractive clustering	6	0.0036	22.0430

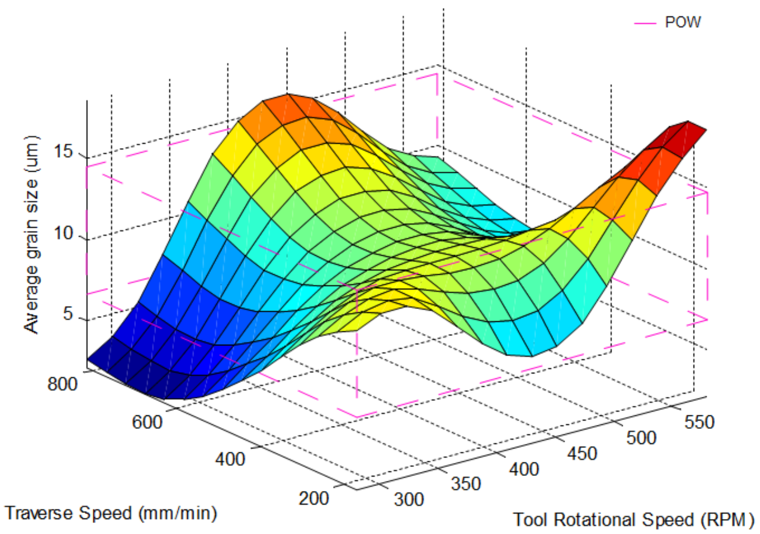

Figure 3.17 The NF sub-process model developed via grid partition to simulate the behaviour of average grain size during the FSW process

An example of the linguistic understanding of the fuzzy-rules presented in Figure 3.18 can be interpreted as follows:

For rule 2: If the tool rotational speed is "LOW" and traverse speed is "MEDIUM" then the average grain size is "SMALL".

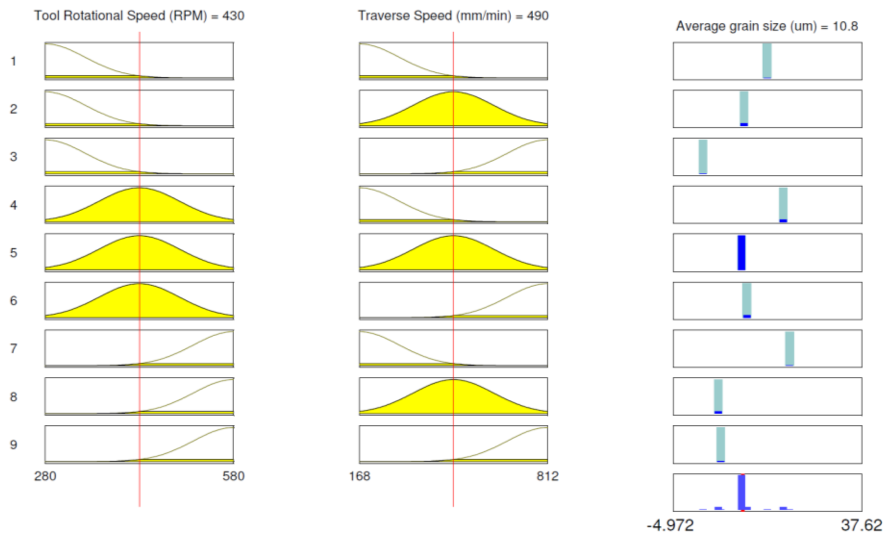

Figure 3.18 Fuzzy-rules and aggregation process created using grid partition techniques to described the behaviour of average grain size during the FSW process

The FSW process results in significant micro evolution, the average grain size behaviour predicted in this model can be compared with micrographs of the pre-weld and post weld materials where the different grain sizes can be identified (Zhang et al., 2011):

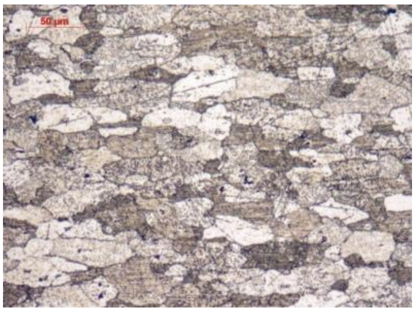

Figure 3.19 Micrographic of the parent material

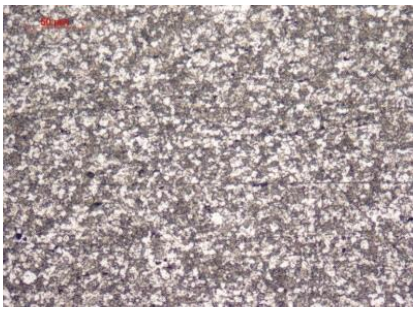

Figure 3.20 Micrographic of the weld at 280rpm and 392 mm/min

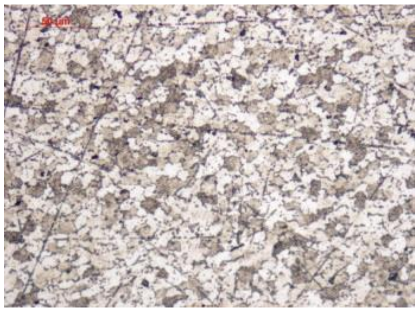

Figure 3.21 Micrographic of the weld at 580 rpm and 348 mm/min

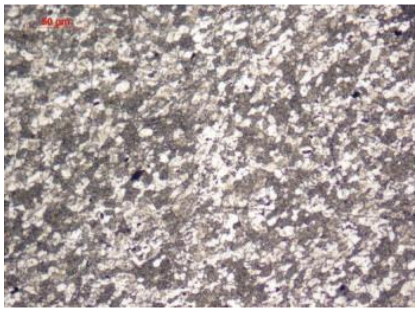

Figure 3.22 Micrographic of the weld at 580 rpm and 812 mm/min

Similar results about the prediction of the average grain size in the nugget zone are reported in (Livan Fratini et al., 2009). The average grain size calculated within this zone is between 15-20 μm which shows a good agreement with the NF model presented in Figure 3.17.

Model 6: Cooling rate

In Model 6, 13 data samples were used for training and 5 for testing (Table 9.9, appendix 2); Figure 3.23 shows a good prediction of the model developed to simulate the cooling rate behaviour during the FSW process. Figure 3.24 shows the 5 fuzzy rules generated to describe the cooling rate of the FSW process. Table 3.8 summarises the performance of this model.

The NF model created to predict the cooling rate, is one of the original contributions of this research investigation, this is the first time that the cooling rate, is calculated with thermal information created during the welding routine.

Table 3.8 Cooling rate model's performance

	Fuzzy rules	RMSE of training	RMSE of testing
Grid partition	9	6.4042	16.8897
Subtractive clustering	5	0.1487	36.7035

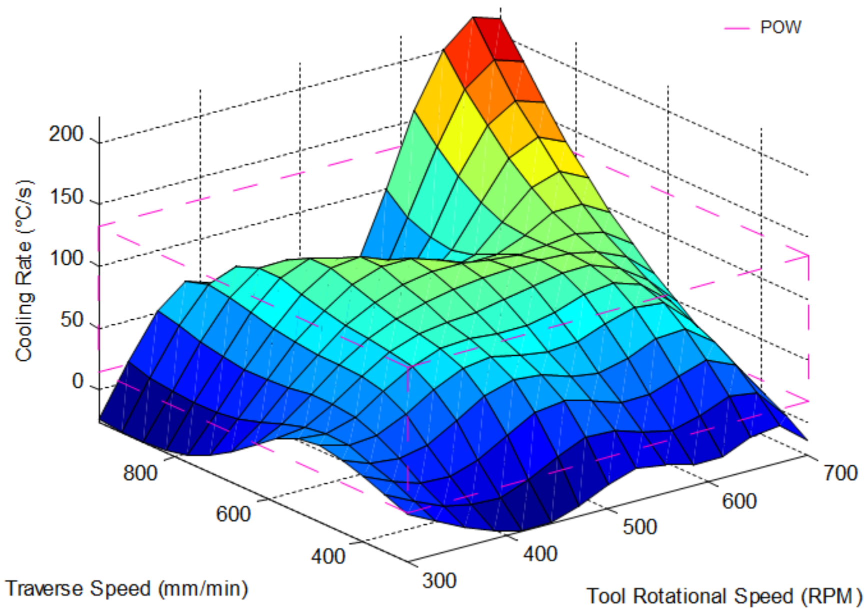

Figure 3.23 The NF sub-process model developed via subtractive clustering to simulate the behaviour of cooling rate during the FSW process

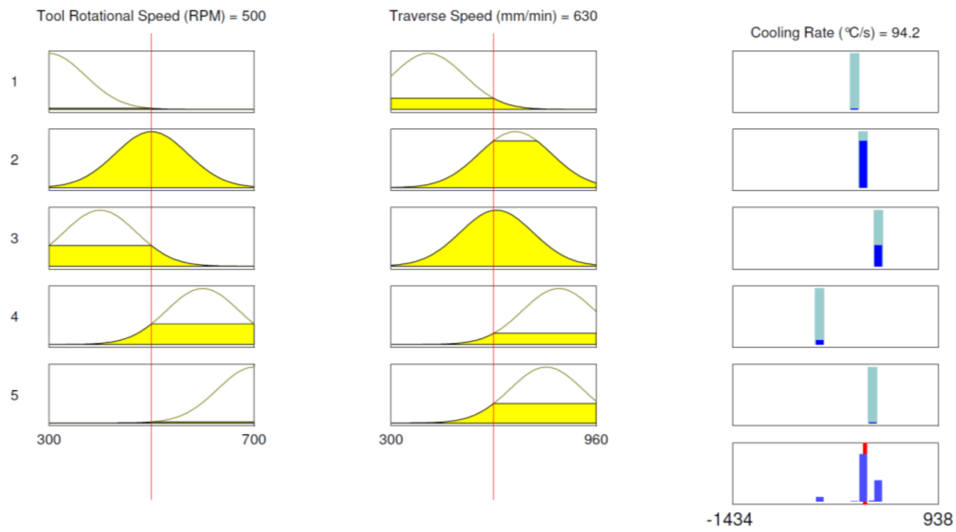

Figure 3.24 Fuzzy-rules and aggregation process created using subtractive clustering techniques to described the behaviour of cooling rate during the FSW process

3.5.3 Multiscale model to predict the quality of the welds during the FSW process

Model 7: Quality of the welds index

For Model 7, 20 data samples were used for training and 5 for testing (Table 9.10, appendix 2). Figure 3.25 shows the simulation response to predict the weld quality. In Figure 3.26, the 4 rules generated to predict the weld quality of welds produced by FSW are presented.

Table 3.9 Weld quality model's performance

	Fuzzy rules	RMSE of training	RMSE of testing
Grid partition	9	0.6616	0.5481
Subtractive clustering	4	0.5146	0.4106

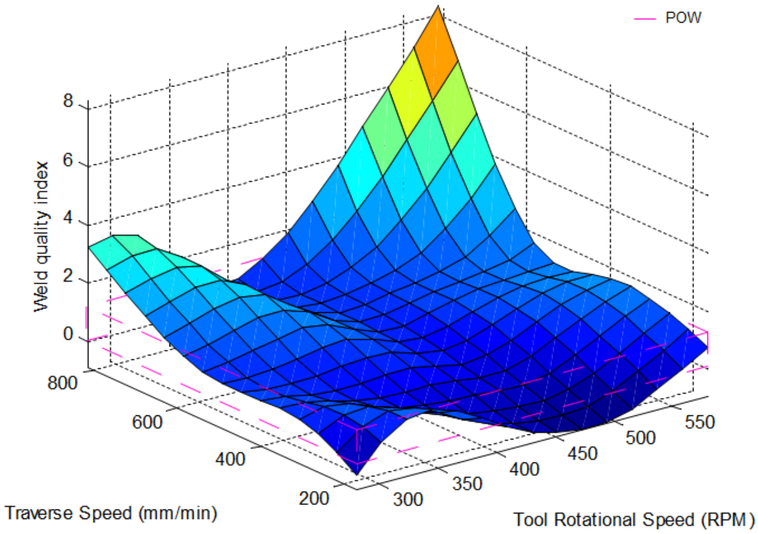

Figure 3.25 The NF sub-process model developed via subtractive clustering to predict the quality of materials welded during the FSW process

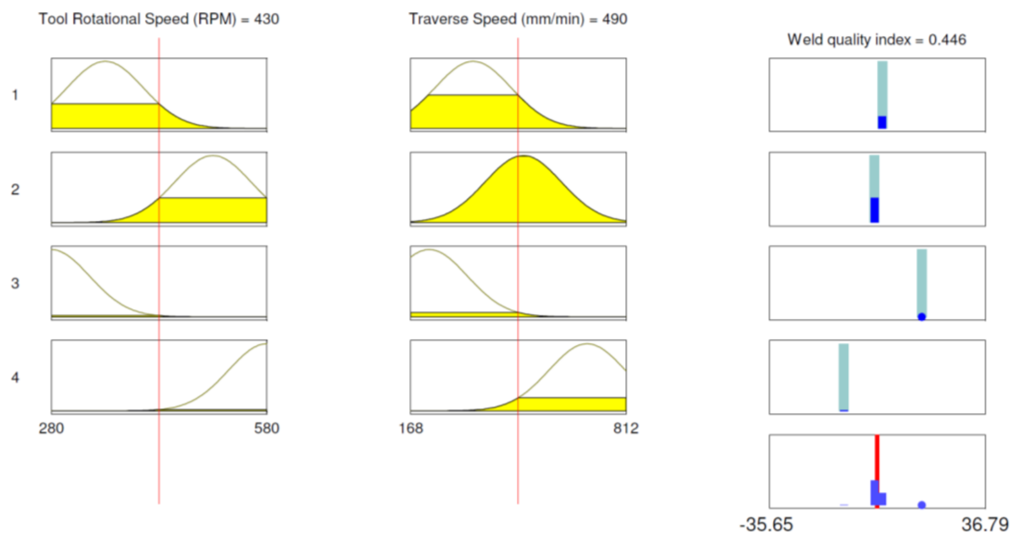

Figure 3.26 Fuzzy-rules and aggregation process created using subtractive clustering techniques to predict the quality of welds produced during the FSW process

The example shown above (in Figure 3.26), demonstrates how the transparency of these models can be translated into linguistic-based knowledge. The model shows how the behaviour of the process variables can significantly influence the quality of the materials welded by FSW. When higher traverse and tool rotational speeds are set, the weld quality of the final product will decrease. In practice, this is because the material cannot be properly stirred if the speeds are too high or too low. This is due to the rate of temperatures needed to plasticise the material. From the point of view of industry, the production of welds with poor quality joints can result in high resource losses and high associated costs (scrap material, rework costs etc.).

Neural-Fuzzy models for monitoring the POW in real-time

Figure 3.27 shows a screenshot of the developed Graphical User Interface (GUI), which is based on LabView V.10. On the left hand side of the GUI window the raw signals (ARTEMIS unit) are plotted and monitored (process settings, internal parameters as well as the tool bending forces), while on the right hand side the software monitors the current performance based on the model-predicted POW. The depicted sample screenshot is based on the NF model previously presented in Figure 3.25, this application predicts in real-time the WQ index based on the current welding speed and tool rotational speed for AA5083 aluminium alloy, 6mm thick, welded with a Tri-flute™ MX tool.

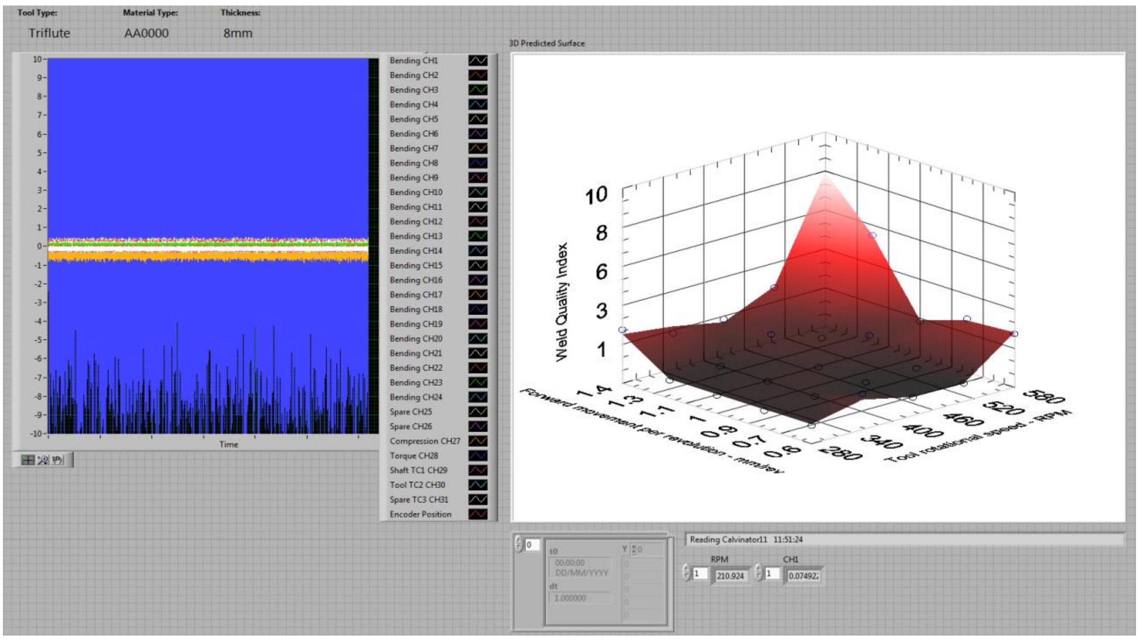

Figure 3.27 FSW model-based monitoring tool, sample screenshot of the graphical user interface

3.6 Summary

In this Chapter, multiscale and data-driven modelling techniques were proposed as tools which can analyse and simulate complex industrial processes. The models presented in this Chapter were developed using NF modelling approaches. These are CI paradigms based on fuzzy systems and NN with the ability to learn from data, predict behaviour of complex systems, and are capable of creating transparent models. It was demonstrated that by using these techniques, a better understanding of complex interactions present in manufacturing processes can be achieved. More importantly, the multiscale models assist the process experts to better comprehend and easily identify the POW's of the system under investigation.

The NF models presented in this Chapter have successfully simulated a complex manufacturing process, in this case FSW. The transparency of the NF models was demonstrated, and the interpretability of these models was exemplified with the use of IF-THEN sentences. It was demonstrated that NF-models can be translated into natural human reasoning which help experts better understand the complex interactions of their systems.

The study of two classification techniques was also evaluated: subtractive clustering and grid partitioning. The aim was to compare the modelling performance resulting from the use of each technique for the given datasets. Subtractive clustering techniques were found to be more flexible than grid partitioning as they can reduce the number of rules. This investigation has shown that NF modelling can accurately predict the behaviour of FSW, even with few parameters and small data samples. The NF models were produced with only two inputs: tool rotational speed and traverse speed, and various process characteristics were also evaluated. The NF models predicted crucial mechanical properties of the materials welded by FSW. Elongation, ROA, YS and UTS were accurately predicted for aluminium alloys AA5083. The microstructure of the material was evaluated by simulating the process data at two different scales:

average grain size and cooling rate. Furthermore, the performance of the models was successfully simulated to predict the quality of welds produced by FSW. It is worth emphasising that the NF models presented in this Chapter are highly transparent. Compared with related studies, the NF models showed a satisfactory accuracy of the variables and the interpretability of the final models has been enhanced with the use of linguistic sentences. The NF models have been confirmed to follow the expected behaviour as predicted by theory and knowledge experts.

As presented in the literature review Section 2.5, NF models have been proposed to analyse complex manufacturing process. NF models of FSW have been previously developed. In this investigation, however, for the first time, a multiscale approach is proposed to gain insights into FSW. This is a significant contribution for process experts as the models have been used as tools to study in depth the complex interactions within the system, as well as its influence over the whole FSW process.

Another important contribution from the simulations presented in this Chapter, was the creation of a NF model which can predict the cooling rate using thermal information from the process. This is a promising approach which can potentially be used for real-time applications.

One of the limitations of this study was the over-fitting of the models, due to the lack of data, the learning process of these models is challenging. In the following Chapters this issue will be addressed by using evolutionary algorithms to optimise the models.

4 A CI modelling and optimisation approach based on spectral-temporal analysis – An application to FSW

Overview

One of the main challenges in manufacturing processes is the detection of behaviour which can affect the process. Many advanced devices, which can collect data, are available, but it is often difficult to extract significant information from the temporal data generated. The analysis of variables which can change through time has been extensively used to extract information from signals which can affect the process. Signals such as vibration, force, temperature, among others, are usually analysed in micro scales using spectral analysis. This technique is widely used as it examines the frequency of a signal to understand its contribution to the whole process. The FFT is extensively used because it allows the spectral analysis of signals, deep understanding of the signal generation and can be used to understand what physical frequency components are contributing to a signal (Bracewell, 1965) . Spectral analysis finds applications in industry and many other fields such as vibration monitoring, economics, meteorology, astronomy, speech analysis, medicine, seismology, control systems among others (Nandagopalan, 1994; Stoica and Moses, 2005). FFT is clearly a form of multiscale representation of the signals (at various scales/frequencies). For this reason, this investigation proposes a spectral analysis framework which analyses the forces generated from a complex manufacturing system, and for the first time, a spectral analysis approach is developed to extract indices which can correlate the frequency-based behaviour of the signals with the quality of the final product. The force's information is extracted from 24 monitoring channels. After extracting this information, a data-driven model-based on NF is created to predict the performance of the system. The novelty of this approach is that the construction of the intelligent NF model describes the manufacturing process with only little information extracted from the signals. Additionally, the proposed approach indicates that the monitoring points can be considerably reduced which can lead to the development of more simple monitoring tools.

The spectral analysis based NF model presented in this Chapter is first developed using a Sugeno-type fuzzy inference system, and then an optimisation of the model is proposed to improve the performance. The optimisation based on GA and NN is proposed to enhance the performance of the spectral analysis based NF model. As predicted, the experiments showed a better performance of the models using the GA-based optimisation. For this reason, the proposed optimisation approach is then used to improve the multiscale models presented in the previous Chapter. The experiments showed a good accuracy for all the multiscale facets of the process under investigation. Furthermore, the optimised models showed potential to use these techniques for online applications, as the computational complexity was reduced by using only five rules to describe the models.

Chapter 4. *A CI modelling and optimisation approach based on spectral-temporal analysis – An application to FSW*

This Chapter will demonstrate the use of NF models to describe complex processes even with small datasets. The spectral analysis based on FFT shows encouraging results to correlate the signals of the process with quality performance. Finally, a GA optimisation, which enhances the performance of the multiscale models, is presented.

4.1 Spectral-temporal analysis and manufacturing processes

Spectral analysis is applied in many fields of engineering, economics, meteorology, astronomy and several others. Spectral analysis permits the study of 'hidden periodicities' in data which in manufacturing processes is normally collected from advance data acquisition devices (Stoica and Moses, 2005). Signals are being generated continuously from industrial processes and many monitoring applications have been developed base on signal analysis. As a result, there is a significant interest in the study of spectral analysis. Spectral analysis is very useful for the examination of frequency content in a signal; this analysis is widely used when trying to understand what physical components are contributing to a signal. Physical quantities such as forces, vibration and temperature can easily represent the effect of frequency from signals.

For the case of FSW, several signal variables such as force, torque and temperature can be recorded during the welding routine. Currently, as reviewed in Sections 2.1.9 and 2.1.10, the data acquisition devices used for FSW can collect high-definition data from different forces involved in the process. Attempts to study the effect that forces can have over the joint and to potentially apply this approach for online applications have been made. For instance, an interesting study presented by (Boldsaikhan et al., 2011), used NN and discrete Fourier transform to evaluate the oscillations of forces, this approach demonstrates the potential of spectral analysis of forces to monitor the FSW in real-time, and more importantly, the study revealed that the frequency patterns from the forces can detect wormhole defects.

4.1.1 Fast Fourier transform

The use of Fourier analysis is very common in industry. One common application is machinery condition monitoring. Fourier analysis is used to gain understanding of the signal generation. More insight is gained from observation of the spectrum, i.e., the signal decomposed as a function of frequency (Purdue-University, 2011). In this investigation, FFT are used to study the forces generated by the ARTEMIS tool. FTT finds the frequency components of a signal in a time domain environment. The spectrum of forces presented in this investigation was created by using the 'fft' function of MATLAB, the details of the algorithm can be found in (MathWorks, 2012).

4.1.2 A neural-fuzzy model-based on spectral-temporal information of FSW

As discussed in the literature review, the cost of test to identify defects on welds is high and implies destroying the tested material. There is also a lack of techniques which can predict (analytical or otherwise) the behaviour of welds or analyse the FSW process in real-time. However, as previously discussed, by using CI and modelling frameworks, model-based structures can be developed to simulate the behaviour of the underlining processes.

This Chapter focuses on a model-based technique as an approach that uses CI methods to build models that describe the behaviour of the FSW process. Data-driven modelling is usually proposed as a lower computational cost method, as compared to FE and CFD which are frequently used to model the FSW process (He et al., 2014). One of the drawbacks of some CI modelling techniques, such as, NN is the lack of interpretability of the resulting models ('black box'). This is because for complex processes, such as FSW, or process with a high amount of numerical data, it is challenging to create more transparent, easier to understand, i.e., linguistic-oriented models. However, as previously discussed, by combining CI modelling techniques with human-cognition-based modelling approaches such as FL and NF systems, hybrid models can be developed to create transparent structures.

In this Section, spectral-temporal process information is analysed to develop transparent and accurate model-based 'process mappings' of signals generated by FSW. For the proposed approach, spectral indices are created directly from high-resolution information recorded using the ARTEMIS tool. This is a novel approach which studies the relationship between the process parameters and the overall quality of the welds. The process parameters include, tool rotational speed, traverse speeds and bending forces (see Figure 4.1).

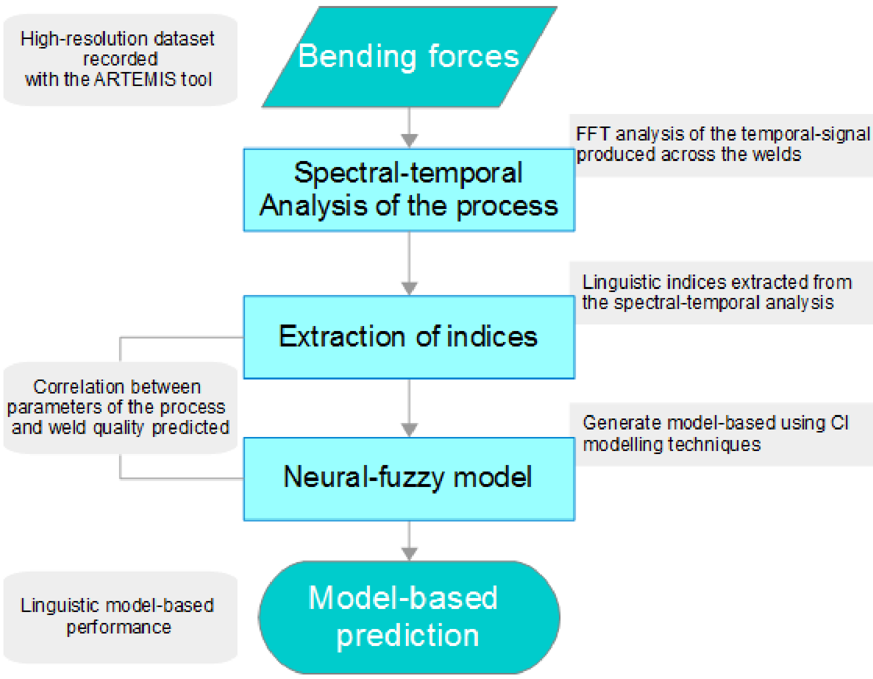

Figure 4.1 NF modelling approach based on spectral-temporal analysis of internal variables of the FSW process

4.1.3 Neural-fuzzy modelling

For the experiments presented in this Chapter, the use of CI Modelling techniques was proposed to create a model-based approach for the monitoring of the FSW process. It is achieved by transforming the data process information into process knowledge (transparency) that may allow deeper study of this complex industrial process. This Section employs NN due to its ability to capture complex patterns in the data, as well as fuzzy systems that offer the ability to develop hybrid models that are transparent to the user. As discussed in the literature review, NF modelling techniques have been successfully applied in the past to model complex industrial processes which are both computationally efficient and highly transparent (Abbod et al., 2006; George Panoutsos and Mahfouf, 2010; Zhang et al., 2011).

FL is an approach to computing based on 'degrees of truth' rather that 'true or false' (1 or 0). The approach attempts to solve problems by trying to mimic human cognition (LA Zadeh, 1965). The main advantage of FL systems for modelling approaches is their transparency and enhanced interpretability of the resulting models via the use of '*linguistic variables*'. Via these systems, it is possible to extract knowledge from data which then can be presented in human-based reasoning terms (linguistic 'IF-THEN' rules). The aim of NF modelling approaches is to combine the transparency of rule-based fuzzy systems, such as FL, with the flexible learning capability of NN.

4.2 Methodology

4.2.1 Experimental data

A high-resolution dataset was recorded during welding trials, at TWI Ltd., using the ARTEMIS tool which collected the high-resolution information of the bending forces for 34 welds of varying process conditions (traverse and tool rotational speeds) see Table 4.2. For each weld, the tool bending forces were measured around 24 points (channels) every 7.5 degrees on the tool circumference. The material used for these trials was 6mm thick of AA5083 aluminium alloy, the welds were performed using the Tri-flute™ MX tool.

The quality of the welded samples was quantified by process experts via four different indices: bend test-root, bend test-face, surface finish and cross sectional inspection. Using expert knowledge, each index was expressed in numerical values between [0 – 3] as follows:

Table 4.1 WQ indices evaluation by process experts

Numerical Value	Expert interpretation
0	Free from identifiable flaws
1	Slight indication/witness
2	Partial failure
3	Complete failure

A final index was then constructed by aggregating the four sub-indices. This overall index measures the ‘Weld Quality’ (WQ) of the joints, it ranges between [0 – 12], where 0 = Good weld quality and 12 = Poor weld quality.

Table 4.2 Quality assessment and process conditions of 34 weld samples performed using the Tri-flute™ MX tool for 6mm thick sheets of AA5083 aluminium alloys

Weld sample	Tool rotational speed (RPM)	Traverse speed (mm/min)	Bend test-root (0-3)	Bend test-face (0-3)	Surface finish (0-3)	Cross section (0-3)	Weld Quality 'WQ' (0-12)
C04	380	304	0	0	0	0	0
C05	380	304	0	0	0	0	0
C06	380	304	1	0	0	1	2
C11	280	168	0	0	0	0	0
C12	280	224	0	0	0	0	0
C13	280	280	0	0	0	0	0
C14	280	336	0	0	0	0	0
C15	280	392	0	0	1	1	2
C16	355	213	0	0	1	0	1
C17	355	284	0	0	0	0	0
C18	355	355	0	0	0	0	0
C19	355	426	0	0	0	0	0
C20	355	497	1	0	0	0	1
C21	430	258	0	0	0	0	0
C22	430	344	0	0	0	0	0
C23	430	430	0	0	0	0	0
C24	430	516	0	0	1	0	1
C25	430	602	0	0	1	0	1
C26	505	303	0	0	0	0	0
C27	505	404	0	0	0	0	0
C28	505	505	0	0	0	1	1
C29	505	606	0	0	0	0	0
C30	505	707	0	0	0	2	2
C31	580	348	0	2	0	0	2
C32	580	464	0	2	0	0	2
C33	580	580	0	1	0	0	1
C34	580	696	0	1	1	3	**5**
C35	580	812	3	1	1	3	**8**
C36	380	304	0	0	0	0	0
C37	380	304	2	0	0	0	2
C38	380	456	0	0	0	0	0
C39	380	532	0	0	0	1	1
C40	380	608	0	0	1	1	2
C41	380	684	0	0	1	2	3

As a consequence of the large quantity of high-resolution data generated in a single weld, the use of spectral-temporal analysis was proposed to analyse the temporal signal of the bending forces. Several 3D frequency spectra plots of the 34 welds were developed to observe the behaviour of the process in the frequency domain (0-15 Hz) across all the 24 channels.

Based on the spectral-temporal analysis, two indices were extracted from the amplitude of the signal to then generate the process model using an ANFIS (Jang, 1993). This approach is proposed to capture spectral-temporal patterns from the tool bending forces of the FSW process, in order to map the non-linear relationships between the process data and the resulting weld quality. The hypothesis predicts that the bending forces will reveal a frequency behaviour which will differentiate the levels of weld quality between the welds. In addition, this modelling approach allows the development of a transparent model structure easy to analyse (in a linguistic format) and with a good accuracy of the WQ. The model-based approach was evaluated using the RMSE as a cost function to calculate the relationship between the bending forces and the predicted response.

4.3 Spectral-temporal analysis of the bending forces extracted from friction stir welded samples

The proposed model-based approach is focused on the spectral-temporal analysis of the high-resolution bending forces recorded via the ARTEMIS tool. The spectral-temporal methodology was developed by using a FFT (MathWorks, 2012) to analyse the temporal signal generated in the 24 channels across the weld, for all the 34 weld samples. The spectral analysis was created using the 'fft' function in MATLAB, the parameters used for the function were:

Table 4.3 FFT sampling settings

Sampling settings	Value	Variable
Sampling frequency	25 (Hz)	Fs
Sample time	1/Fs (Hz)	T
Time vector	Initial time welding : T : Final time welding	t
Length of signal	1024	L

After the spectral-temporal analysis of the 34 welds, 3D frequency spectra plots, in the frequency domain from 0 to 15 Hz, were created to observe the behaviour of the process across all the monitoring channels. The analysis of the 3D plots showed the high correlation of the amplitude of the signal with the quality of the weld, which is influenced by the process speeds. All the welds above 580 rpm presented defects. Spectral samples of (a) a defect-free weld, (b) a weld with flaws, and (c) a weld with poor quality are shown and explained below.

Figure 4.2, illustrates the original signal from the bending forces of weld sample C11, the plot is an example of only a single channel, in this case the plot shows channel 12. In the same figure, the amplitude spectrum generated using FFT is plotted. For a better visualisation of the behaviour of the 24 channels for each weld, 3D plots were generated. The spectral-signal of all channels for weld sample C11 is illustrated in Figure 4.3. This weld was evaluated as defect-free with WQ = 0. The settings of this weld were: tool rotational speed of 280 rpm and traverse speed of 168 mm/min. For this weld sample the amplitude of the signal can be clearly observed across the 24 channels.

A different exemplification of the amplitude for a weld with flaws is presented in Figure 4.4; the plots in this figure show the original signal from the bending forces of weld sample C24, for channel 09, and the amplitude spectrum for that weld sample. The amplitude spectrum of all channels for weld sample C24 is illustrated in Figure 4.5. This weld was evaluated as weld with flaws WQ = 1 .The settings used for this weld sample were: tool rotational speed of 430 rpm and traverse speed of 516 mm/min.

The amplitude behaviour for a weld with poor quality, WQ = 8, is presented in Figure 4.6, the original signal from the bending forces of weld sample C35, for channel 12, and the amplitude spectrum generated using FFT are also shown in this figure. While, in Figure 4.7, it can be observed that the parameters of the welds can have a significant influence in the spectral behaviour of the bending forces. This figure shows the amplitude spectrum of all channels for weld sample C35. The settings used to produce this weld sample were: tool rotational speed of 580 rpm and traverse speed of 812 mm/min.

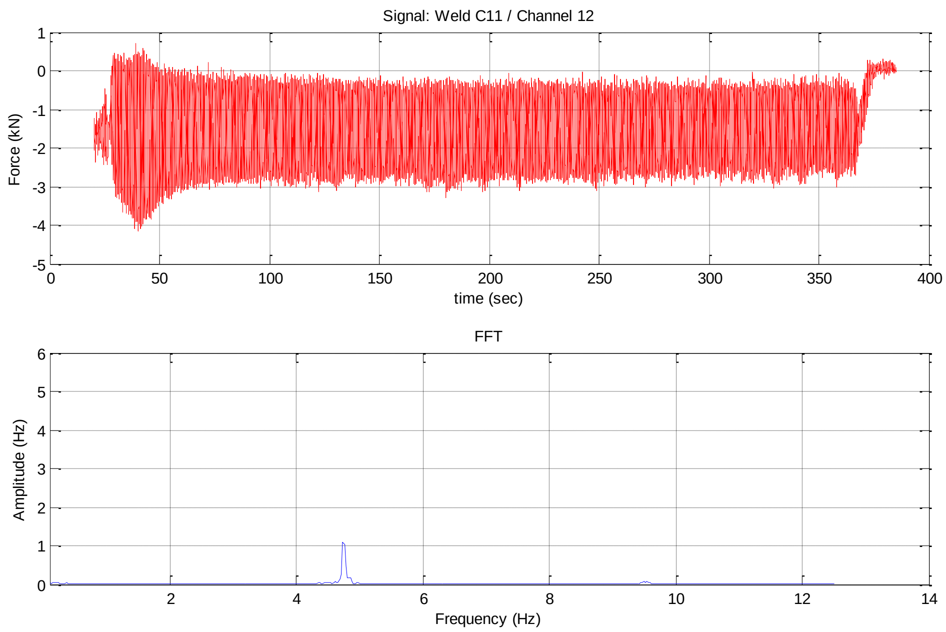

Figure 4.2 Amplitude and time domain spectrum generated from weld sample C11 in channel 12

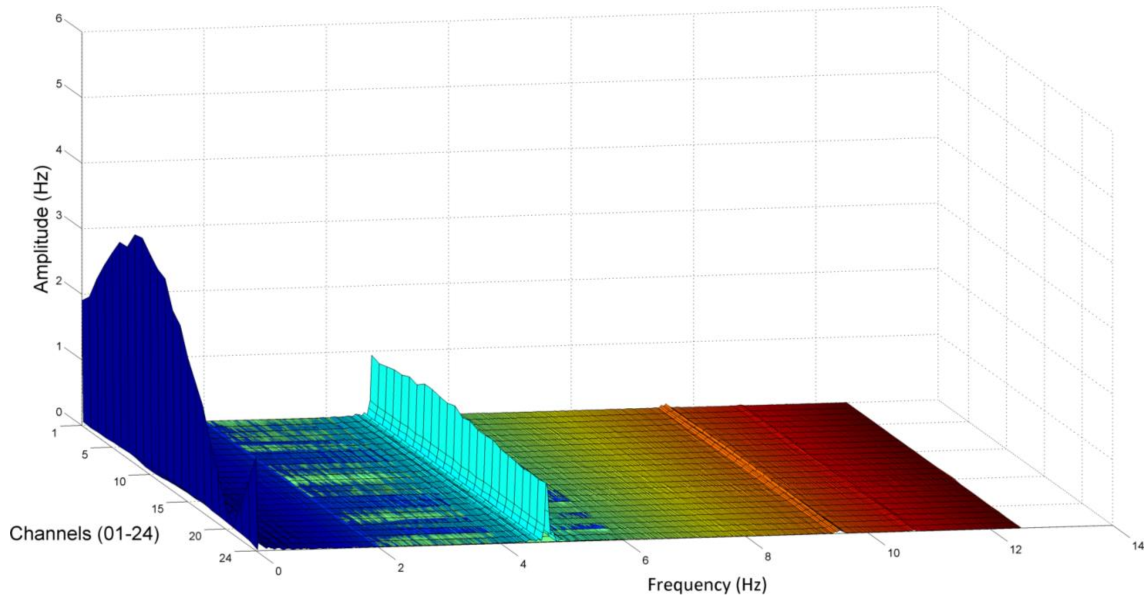

Figure 4.3 Amplitude spectrum of the high-resolution weld sample C11, WQ = 0 produced at 280 rpm, 168 mm/min

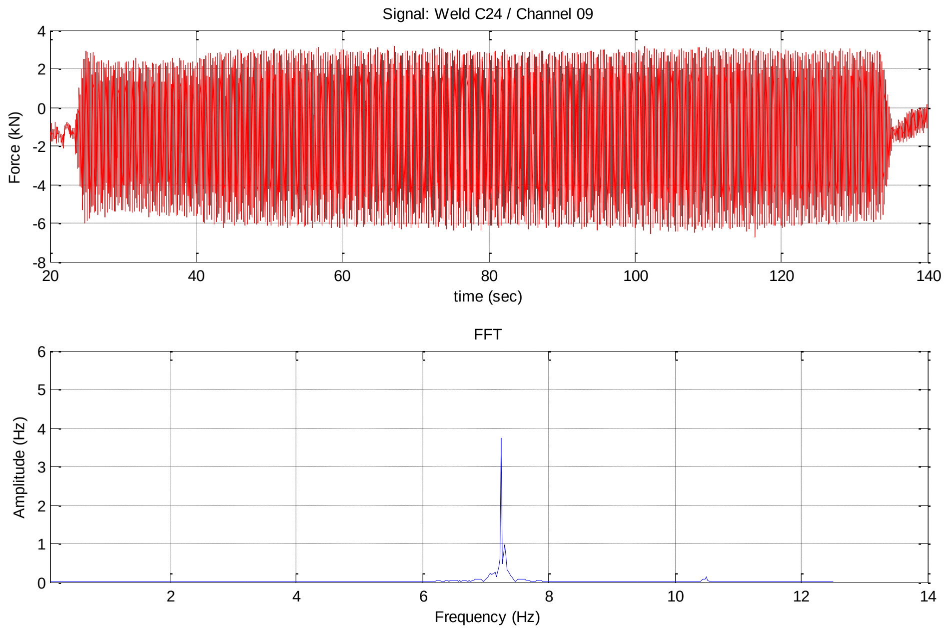

Figure 4.4 Amplitude and time domain spectrum generated from weld sample C24 in channel 09

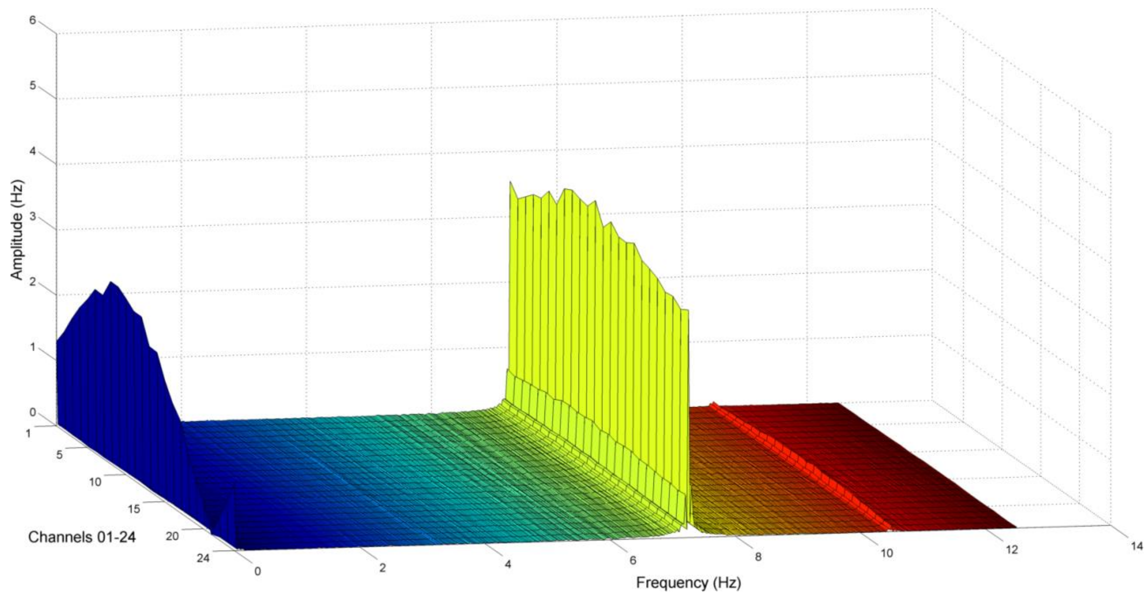

Figure 4.5 Amplitude spectrum of the high-resolution weld sample C24, WQ = 1 produced at 430 rpm, 516 mm/min

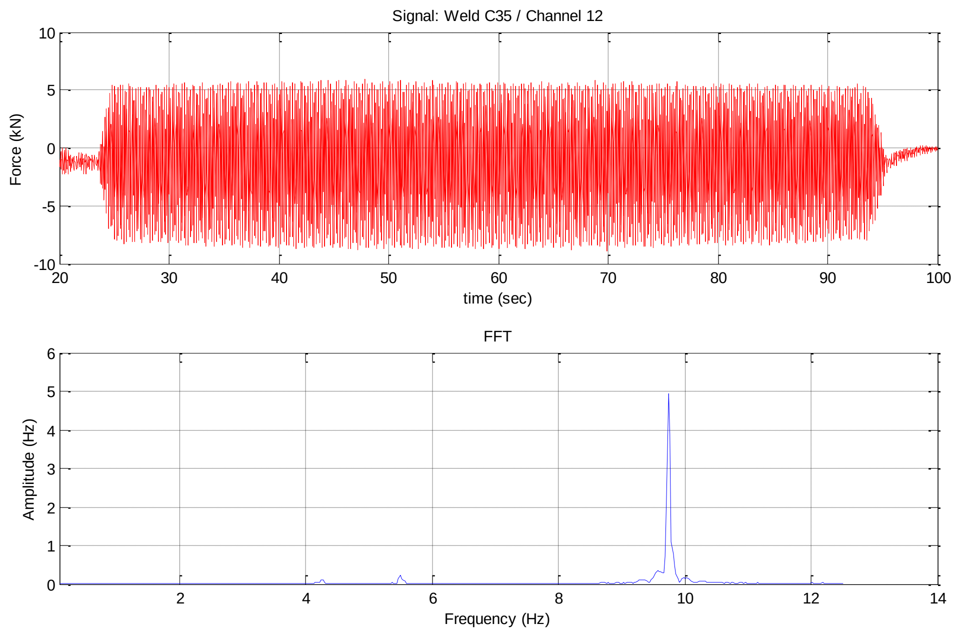

Figure 4.6 Amplitude and time domain spectrum generated from weld sample C35 in channel 12

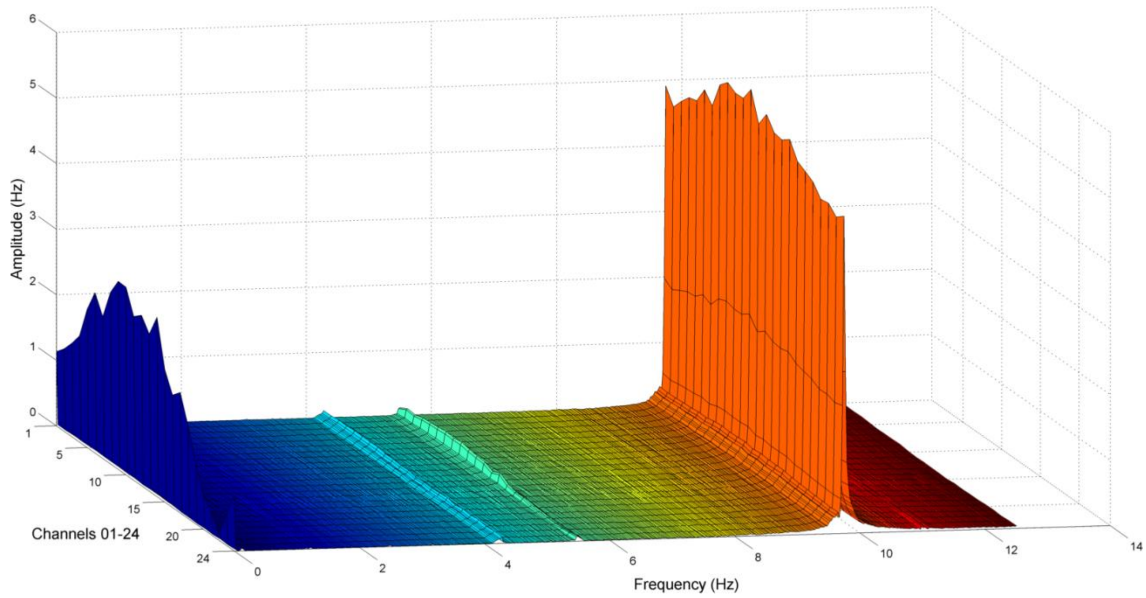

Figure 4.7 Amplitude spectrum of the high-resolution weld sample C35, WQ = 8 produced at 580 rpm, 812 mm/min

As can be observed from the 3D spectral plots, the temporal signal across the frequency domain shows 'peaks' in the amplitude values related with the process parameters. The challenge, from a data-driven modelling and computational point of view is to capture the spectral patterns and use them to directly evaluate weld quality. Within the 3D spectral plots of the 34 welds, seven significant 'peaks' were identified on the spectral frequency across various signals. The 'peaks' identified were analysed in two dimensions (amplitude vs. frequency) the behaviour is illustrated as follows:

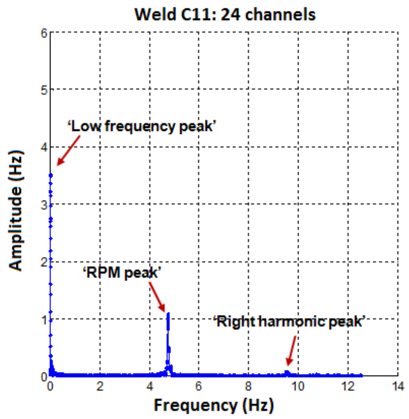

Figure 4.8 The amplitude behaviour of three peaks out of the seven peaks identified within the spectral analysis

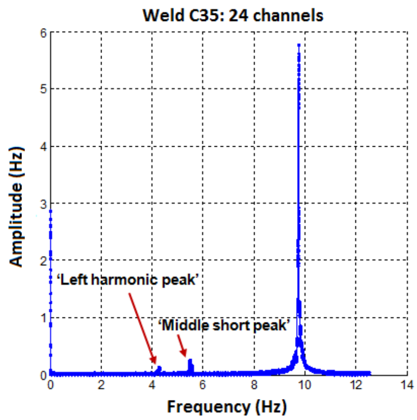

Figure 4.9 The amplitude behaviour of two peaks out of the seven peaks identified within the spectral analysis

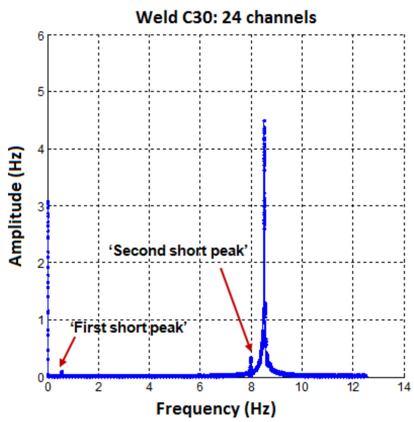

Figure 4.10 The amplitude behaviour of two peaks out of the seven peaks identified within the spectral analysis

As illustrated in Figure 4.8, Figure 4.9, and Figure 4.10, the frequency peaks appeared at different points of the frequency domain, the behaviour of the seven frequency peaks with respect to the amplitude is explained as follows:

i. **Low frequency peak** [⬇]. Appears in all welds at the beginning of the signal (Figure 4.8).
ii. **RPM peak** [⋀]. Appears in all welds at the RPM frequency value (based on the tool rotational speed setting) (Figure 4.8).
iii. **Right harmonic peak** [➜]. Appears after the 'RPM peak' (Figure 4.8).
iv. **Left harmonic peak** [⬅]. Appears before the 'RPM peak' (Figure 4.9).
v. **First short peak** [➡]. Appears immediately next to the 'Low frequency peak' (Figure 4.10).
vi. **Second short peak** [▶]. Appears directly adjacent to the 'RPM peak', just before the peak appears (Figure 4.10).
vii. **Middle short peak** [➤]. Appears directly adjacent to the harmonic peak ('Left harmonic peak' and 'Right harmonic peak'), shortly after the peak appears (Figure 4.9).

The spectral analysis of the bending forces revealed a potential to correlate frequency features to weld quality. An exhaustive analysis of the spectral signals of the 34 weld samples across the 24 monitoring points was performed; interesting behaviour related with the amplitude was identified and important information was extracted, Table 4.4 summarises the significant spectral features that contribute to the weld quality.

Table 4.4 Analysis of the behaviour of the peaks across the 24 channels

Weld Sample	Tool rotational speed (RPM)	Traverse speed	Weld quality Index (WQ)	Monitored points (Channels)																							
				CH01	CH02	CH03	CH04	CH05	CH06	CH07	CH08	CH09	CH10	CH11	CH12	CH13	CH14	CH15	CH16	CH17	CH18	CH19	CH20	CH21	CH22	CH23	CH24
C11	280	168	0									↓▲→															
C12	280	224	0								→	↓			▲												
C13	280	280	0						→			↓			▲												
C14	280	336	0					→				↓			▲												
C15	280	392	2							→		↓			▲												
C16	355	213	1									↓→			▲												
C17	355	284	0									↓			▲			→									
C18	355	355	0									↓			▲					→							
C19	355	426	0									↓			▲			→									
C20	355	497	1									↓			▲					→							
C21	430	258	0									↓			▲		→										
C22	430	344	0									↓			▲→												
C23	430	430	0								↓				▲→												
C24	430	516	1								↓				▲←		→										
C25	430	602	1									↓			▲		→	←									
C26	505	303	0					⇨			▶	↓			▲												
C27	505	404	0						⇨			↓▶			▲												
C28	505	505	1					⇨				↓			▲		▶										
C29	505	606	0								↓⇨	▶			▲												
C30	505	707	2								⇨▶	↓			▲												
C31	580	348	2								←	↓➤			▲												
C32	580	464	2					←		➤		↓			▲												
C33	580	580	1								←	↓➤			▲												
C34	580	696	5						←		↓	➤			▲												
C35	580	812	8								←	↓➤			▲												
C04	380	304	0									↓←			▲	→											
C05	380	304	0												▲↓		→										
C06	380	304	2												▲↓				→								
C36	380	304	0									→			▲↓												
C37	380	304	2						←			↓			▲→												
C38	380	456	0	→								↓			▲												
C39	380	532	1									↓			▲	→											
C40	380	608	2						↓						▲	→											
C41	380	684	3						↓						▲	→											

The activity zone, between channel 5 and channel 17 was analysed using a correlation approach (Pearson's coefficient) (MathWorks, 2011) in order to establish the one-to-one relationship of these channels as compared to the weld quality of the process. Based on the correlation results of the channels and the amplitude of the signal, channel 12 showed a high correlation to the weld quality, this can also be observed in Table 4.4. From this analysis, it is evident that not all the ARTEMIS channels need to be used for weld quality prediction, which can lead to a simplified ARTEMIS unit instrumentation.

The relation between channel 12 and weld quality was evaluated using Pearson's correlation approach, the calculated value obtained was 0.8295 (high correlation of the variables evaluated) also, the peak analysis across the welds samples (3D spectra) identified the amplitude of the 'RPM peak' as a possible influence for the prediction of the weld quality, this peak also appears in all the 34 welds.

4.3.1 Neural-fuzzy model-based on spectra-temporal analysis of FSW

The process of directly linking spectral indices to weld quality and embedding information in a model/mathematical structure is relatively complex. The use of FL, however, allows this 'translation' to be done via the use of expert knowledge (FSW experts, modelling experts). It is possible to appreciate the complexity and non-linearity of the resulting data (spectral-temporal analysis). This Section describes the link between the indices extracted from the bending forces to develop an accurate NF model that predicts the behaviour of the FSW process. This approach demonstrates the potential of using CI modelling techniques as a tool to transform data process information into an efficient computational model.

After analysing the behaviour of the amplitude of the rpm signal, two parameters were identified as possible candidates for directly influencing on the quality of the process: (i) *maximum amplitude value* and (ii) *limit 1* (+2% of amplitude value). Using these parameters, two indices were extracted directly from the spectral-temporal analysis:

i. Index 1: represents the amplitude value from *limit 1*
ii. Index 2: represents the *maximum amplitude value*

By using these indices two datasets were created via cross-validation to develop the NF model. Cross-validation is a statistical method of evaluating and comparing learning algorithms by dividing all available data into subsets (Jerome et al., 2001). Leave 'x' out cross-validation is a procedure used when the available data samples are sparse; this procedure is proposed for performance estimation and model selection to avoid over-fitting.

For the original dataset, two subsets were created, 25 weld samples were used to train the model and the rest of the data to validate the model (see Table 4.5). The process of 'leave 9 out' cross-validation was employed and repeated several times per model in order to establish the best model training regime.

Table 4.5 Dataset used to create a spectral analysis based NF model of FSW.

	Weld sample	Index 1 (Max Amp)	Index 2 (Amp. at Freq. +2%)	Weld Quality
TRAINING DATA	C11	1.1346	0.0374	0
	C12	2.2573	0.1152	0
	C13	2.7225	0.1551	0
	C14	3.4049	0.2019	0
	C15	3.7965	0.2628	2
	C16	1.8744	0.1217	1
	C17	1.7298	0.0339	0
	C18	2.0752	0.0957	0
	C19	2.8183	0.2056	0
	C20	3.1397	0.0559	1
	C21	2.5185	0.0803	0
	C22	2.9208	0.1438	0
	C23	3.5618	0.1074	0
	C24	4.1595	0.1491	1
	C25	3.7177	0.3444	1
	C26	2.7711	0.1518	0
	C27	3.7057	0.1523	0
	C28	3.2342	0.2039	1
	C29	4.4280	0.2320	0
	C30	4.4956	0.2403	2
	C31	3.5349	0.0088	2
	C32	4.1610	0.0934	2
	C33	3.8975	0.1451	1
	C34	4.0199	0.2118	5
	C35	5.7697	0.2940	8
TESTING DATA	C04	2.1678	0.0313	0
	C05	2.5312	0.0749	0
	C06	2.9524	0.1961	2
	C36	1.9780	0.0607	0
	C37	1.4899	0.0296	2
	C38	2.9819	0.1700	0
	C39	2.8468	0.0855	1
	C40	4.1959	0.0329	2
	C41	4.7754	0.2532	3

By using both, (i) the new indices extracted from the spectral analysis and (ii) the weld quality assessment, a NF model was created to map the non-linear relationships between the process data and the weld quality.

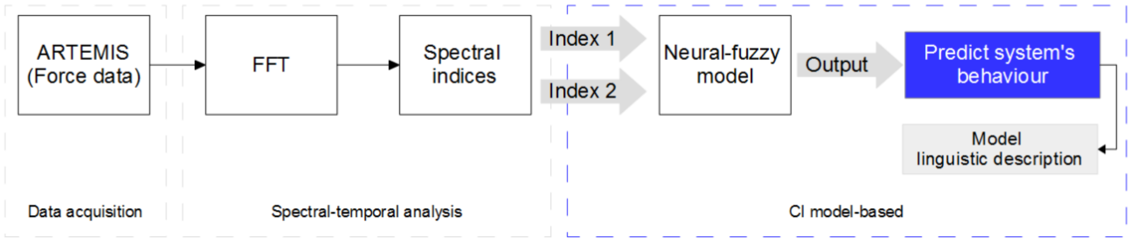

Figure 4.11 Modelling structure developed for the performance of quality of the FSW process based on spectral analysis

As illustrated in Figure 4.11 , the fuzzy-model structure was created based on the spectral-temporal dataset of 34 high-resolution weld samples, with 2 inputs: Index 1, Index 2 and one output: weld quality. The accuracy of the fuzzy model-based was evaluated using the RMSE as a cost function.

For these models, the RMSE was used to calculate the error between the weld quality measured (real industrial data) and the weld quality predicted (NF model) for both training and testing datasets. The RMSE of training data calculated was 0.99245 (Figure 4.12) and the RMSE calculated for the testing data was 1.0942 (Figure 4.13), the performance of the weld quality predicted can be observed in the following figures.

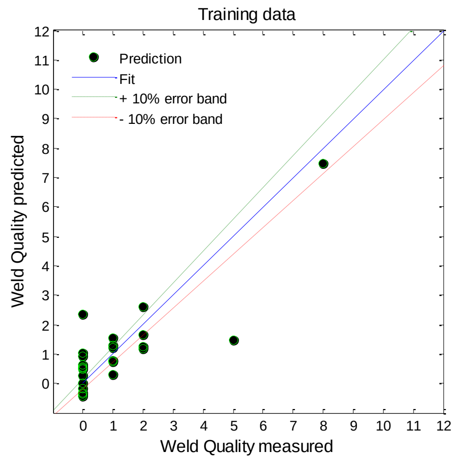

Figure 4.12 Predicted output of the dataset used to train the model

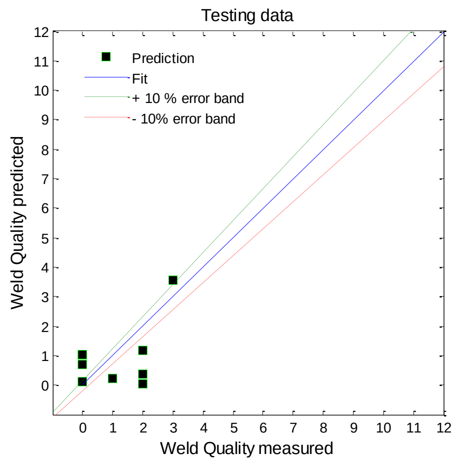

Figure 4.13 Predicted output of the dataset used to test the model response

The resulting simulations, illustrated in Figure 4.14, show a relatively good performance in the prediction of the weld quality, it can be observed that the model extrapolates in a certain area, resulting in negative values; this is due to lack of data in the extrapolated area. In this case, the model naturally estimates beyond the original range.

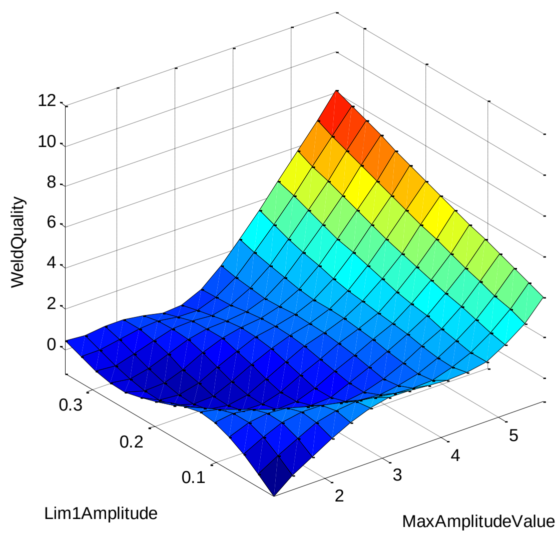

Figure 4.14 Model-based developed using NF systems, it can be appreciated the good accuracy the model to predict the WQ performance with the information from just one channel (channel 12)

The enhanced interpretability of the model can be demonstrated in the linguistic rule-based structure generated to predict the weld quality (Figure 4.15).

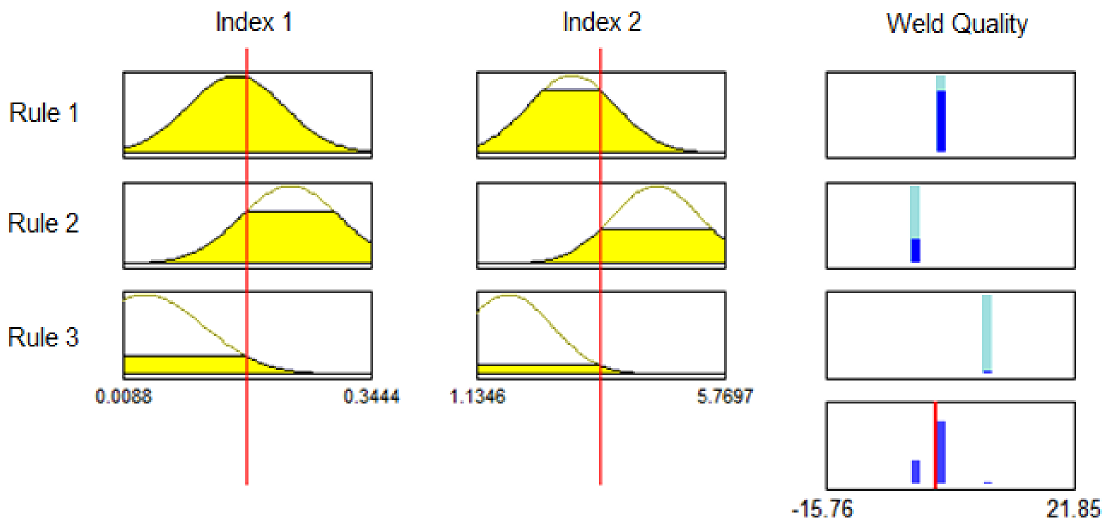

Figure 4.15 The linguistic rule-based structure and aggregation process created to predict the WQ of the FSW process with 2 indices extracted from the spectral analysis

As it is shown in Figure 4.15, three linguistic rules were developed to predict the quality of welds produced by FSW. The developed rules can be interpreted as follows:

1. If **Index 1** is 'high' and **Index 2** is 'medium-high' then **WQ** is 'medium'. (Weld with flaws)
2. If **Index 1** is 'medium-high' and **Index 2** is 'medium' then **WQ** is 'low. (Defect-free weld)
3. If **Index 1** is 'low' and **Index 2** is 'low' then **WQ** is 'large'. (Poor quality of welds)

Overall, in this Section, a NF model-based approach was successfully developed allowing the deep analysis of the performance and the behaviour of the FSW process.

4.4 Optimisation of the neural-fuzzy models using genetic algorithms

At this stage, CI approaches have been applied to demonstrate the ability of adaptive NF inference systems to simulate the behaviour of FSW process. The limitations of these approaches, however, concern mainly in the rule generation. Such a complex process requires the study of more advanced learning algorithms that can improve the models. As reviewed in Section 2.4, the use of intelligent hybrid approaches combining RBF neural networks with learning algorithms such as Fuzzy C-Means (FCM) and GA is widely applied in data-driven modelling due to its capability and computational efficiency.

In this Section, a model-based framework is proposed using the FCM algorithm to initialise the RBF network structure. Due to the absence of any differential equations describing the hybrid system, a GA was used for the optimisation of the RBF (Figure 4.16). Its parameters are subsequently optimised using a GA as introduced in the literature review Section 2.4.3.

Initial Structure

To generate the initial structure of the model and assign the initial conditions for the optimisation, the training dataset is partitioned into multi-dimensional clusters of information using the FCM algorithm, subsequently the training dataset is normalised between [-1 and 1]. FCM is frequently used in modelling approaches as a result of its ability to group and form clusters of data that have similar attributes. As shown in (Bezdek, 1981), by presenting a input-output dataset and assigning the number of clusters, the algorithm creates a list of optimal centres (Nefti and Djouani, 2002a, 2002b). With this information, the initial rule-base for the RBF neural network (centres (c), sigma (σ) and weights (ω) values) can be extracted as detailed in (Zhang and Mahfouf, 2007). The FCM methodology is used here as it conveniently creates FL clusters that can be used directly in the RBF system at low computational processing cost. For the proposed GA-RBF model approach, the number of clusters corresponds to the number of rules. The best response for the welding datasets was obtained with five clusters and sigma value of 0.3 (see Table 4.6).

Optimisation

A GA is used as an optimisation tool that searches for the optimum solution (rules and membership functions) for the RBF neural network structure given a training dataset. The integration of GA, NN and Fuzzy Systems has been used to train and learn complex and non-linear input-output mappings. As discussed in the literature review, Section 2.4, the capability of RBF-NN and GA algorithm to analyse complex systems, learn from information, and seek accurate modelling structures has been successfully applied in previous studies (Linkens and Nyongesa, 1996). Several approaches have been proposed to optimise RBF neural networks using GAs. The optimisation presented in this Chapter is similar to the one shown in (Billings and Zheng, 1995), where the genes to build the chromosomes are defined based on the RBF network weights(membership functions width, membership functions centre, output weights).

Using the information obtained from the FCM, the variables to optimise (N_{vars}) and the structure of the chromosome can be defined. The initial population ($InitPop$) is built as follows:

$$p_1 = (c_1, \dots, c_r, \sigma_1, \dots, \sigma_r, \omega_1, \dots, \omega_r)\ r = number\ of\ rules,$$

$$chromosome = [p_1, \dots, p_{Nvars}]$$

$$InitPop = N_{pop} \times N_{vars}$$

Where, N_{pop} is the population size, in this case, $N_{pop} = 80$, centres (c), sigma (σ) and weights (ω) values are the rule-base for the RBF neural network and each chromosome represents the whole system.

The GA evaluates the fuzzy model structure by minimising the error between the desired output and the trained output. The fitness function is computed the RMSE.

During the evaluation of the fitness function, the GA generates possible solutions for the RBF. Using Equation 2.3 the RBF computes the output of the system. When the termination criterion is achieved, the optimisation routine stops and the final output of the fuzzy model can be obtained.

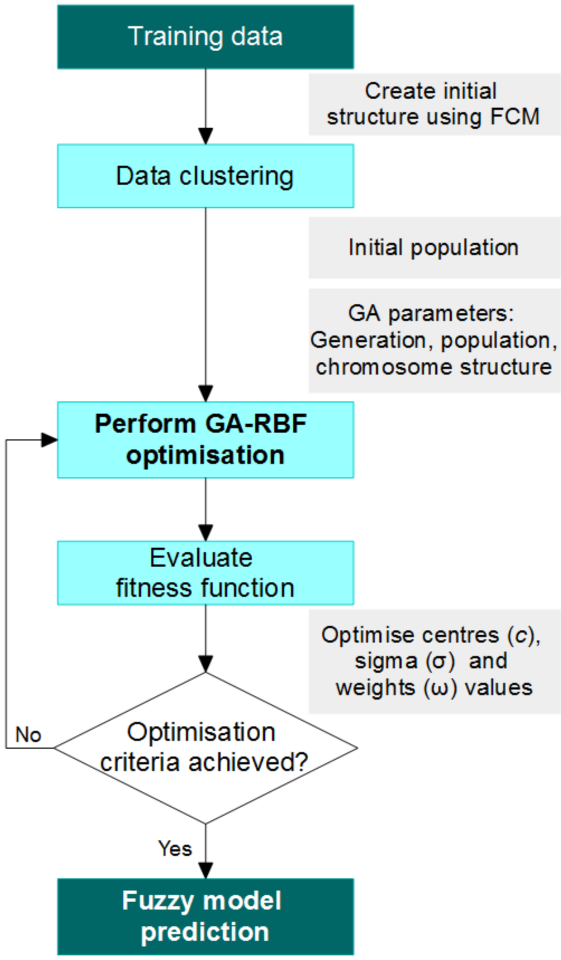

Figure 4.16 Flow chart of the suggested GA-RBF optimisation

This GA-RBF optimisation was proposed in this Chapter to improve the spectral model and also to enhance the multiscale models presented in Chapter 3. The results are resumed in the following Section.

4.4.1 Optimisation of the FSW models using a GA-RBF intelligent hybrid approach

The aim in this Section is to demonstrate the benefits of the proposed GA-RBF optimisation and its ability to improve the efficiency of the NF models previously produced using ANFIS. For the first set of experiments, the training dataset used was based on the spectral analysis obtained in Section 4.3.1, using the two indices as inputs to predict one output, in this case, weld quality. First, the model was presented with the training data (Table 4.5) for 3 rules, its performance was analysed several times increasing the number of rules. As can be observed in Table 4.6, the best response for the welding datasets was obtained with 5 rules.

Table 4.6 The GA-RBF performance evaluation of spectral indices

	RMSE of training	RMSE of testing
3 Rules	0.6130	0.7920
5 Rules	**0.6150**	**0.6600**
10 Rules	0.5450	0.7270

Based on the optimised GA-RBF model from the spectral-temporal analysis, a second set of experiments was performed to improve the response of the multiscale models presented in Chapter 3. The training datasets from the previous created multiscale models were evaluated in this Section in order to demonstrate how the proposed GA-RBF hybrid approach can improve the response and learning process of the models developed to describe the FSW process. The improved fuzzy models were performed using 2 inputs (tool rotational speed and traverse speed) and one output which describe the various sub-processes of FSW (elongation, ROA,UTS, YS, average grain size, cooling rate and WQ). A summary of the improved models is presented in Table 4.7. As can be observed, the overall behaviour of the models shows a clear improvement of the response.

Table 4.7 Comparison of GA-RBF vs. ANFIS performance of the multiscale FSW models

Fuzzy model evaluated	ANFIS model's accuracy			GA-RBF model's accuracy			
	Fuzzy-rules	RMSE of training	RMSE of testing	Fuzzy-rules	RMSE of training	RMSE of testing	Time training routine (sec)
Spectral indices	3	0.9925	1.0942	5	0.6150	0.6600	111.16
Elongation	7	0.0608	4.6683	5	0.3510	0.7380	686.51
ROA	9	1.6500	5.0381	5	0.4620	0.8180	955.68
UTS	9	13.6031	19.0387	5	0.4800	0.8710	464.58
YS	7	0.0023	1.9643	5	0.3350	0.7080	476.02
Average Grain Size	9	0.0002	2.4401	5	0.4010	0.7730	388.72
Cooling Rate	5	0.1487	36.7035	5	0.1820	0.7920	665.68
WQ	4	0.5146	0.4106	5	0.4280	0.7230	388.72

The use of GA is usually proposed to ensure a good performance and better prediction of the NF models. In this case, the model performance was better for each prediction. It was conclude, however, that the generation of more samples in the area of poor quality (WQ > 4) will be helpful for the development of even more accurate models.

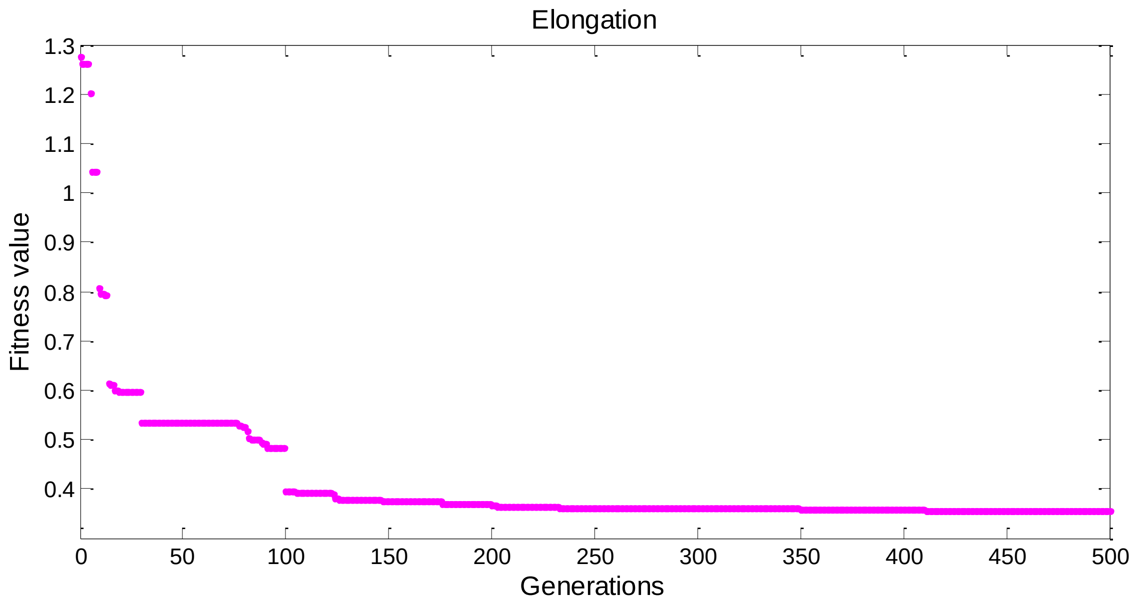

Figure 4.17 Fitness vs. Generations to optimise % elongation of FSW with population size = 80. Elapsed time for training = 686.51 sec

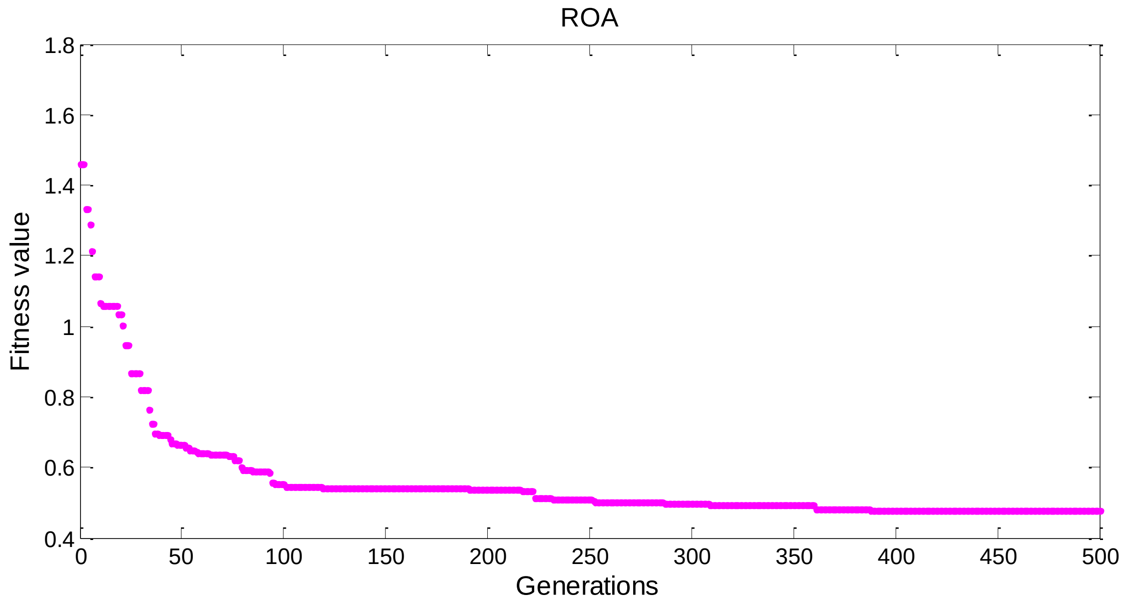

Figure 4.18 Fitness vs. Generations to optimise ROA of FSW with population size = 80. Elapsed time for training = 955.68 sec

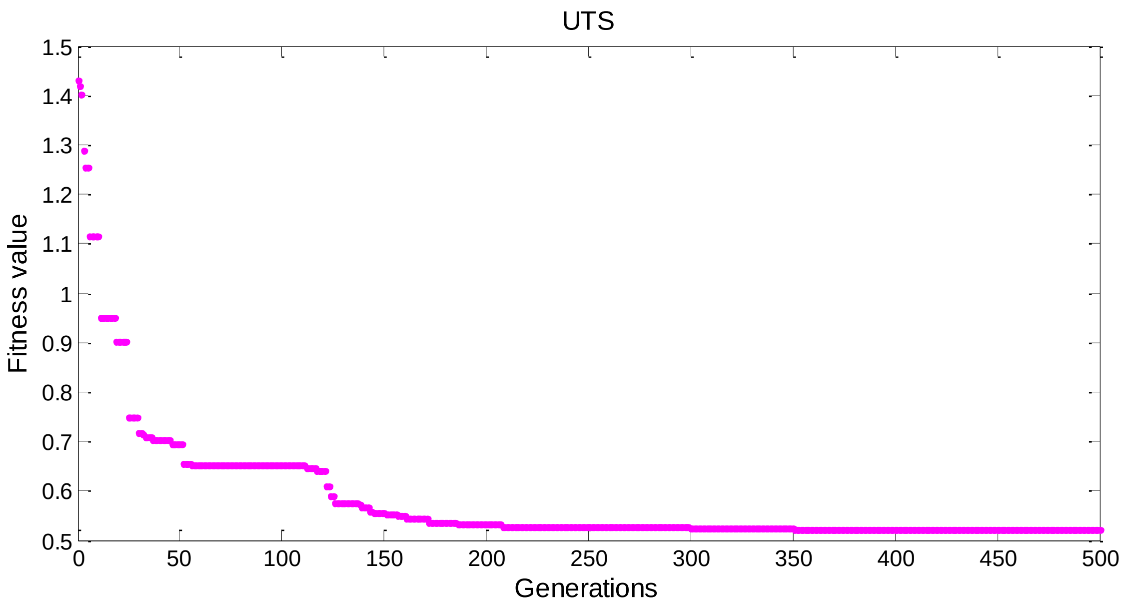

Figure 4.19 Fitness vs. Generations to optimise UTS of FSW with population size = 80. Elapsed time for training = 464.58 sec

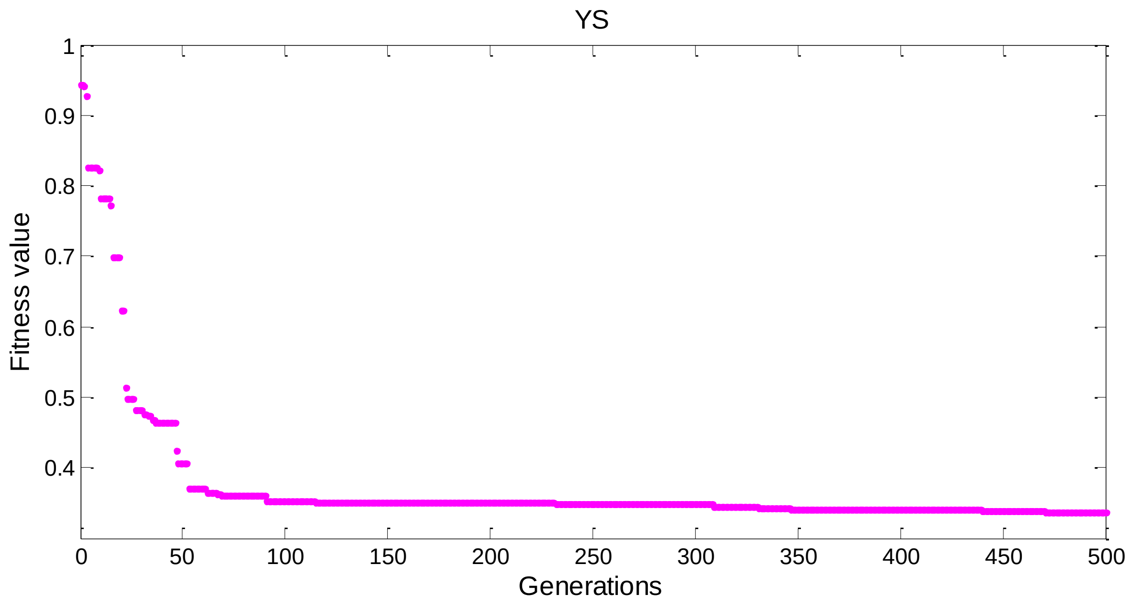

Figure 4.20 Fitness vs. Generations to optimise YS of FSW with population size = 80. Elapsed time for training = 476.02 sec

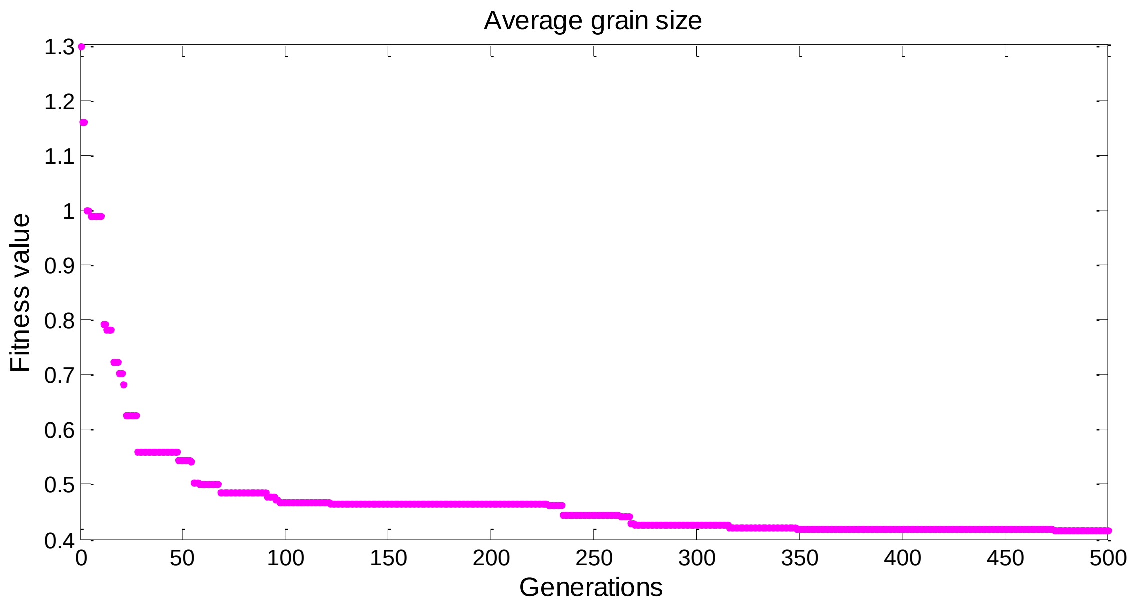

Figure 4.21 Fitness vs. Generations to optimise Average grain size of FSW with population size = 80. Elapsed time for training = 388.72 sec

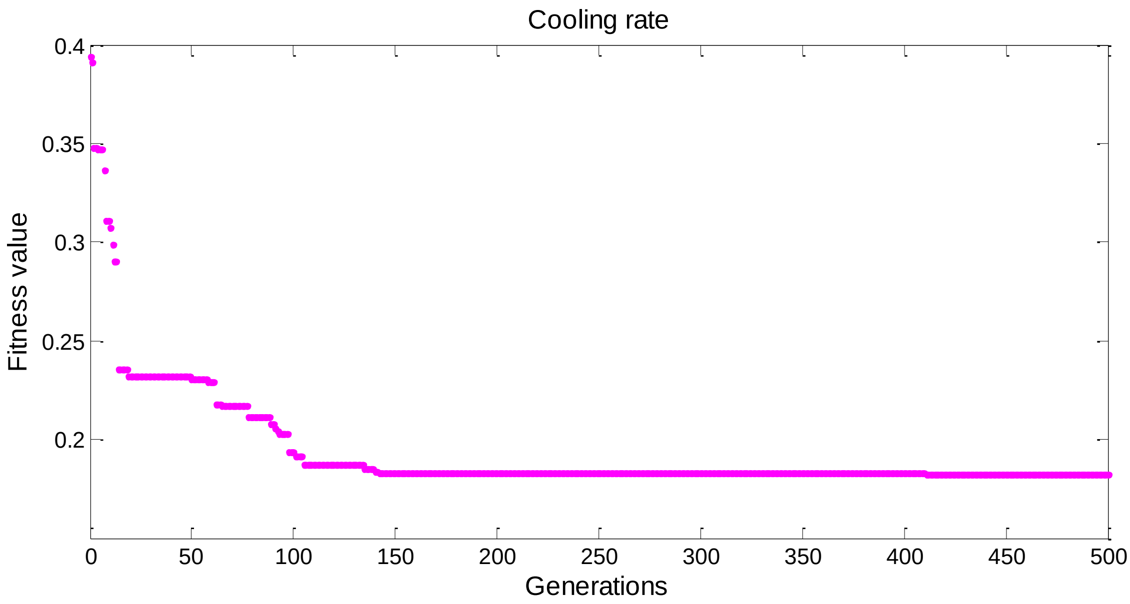

Figure 4.22 Fitness vs. Generations to optimise Cooling rate of FSW with population size = 80. Elapsed time for training = 665.68 sec

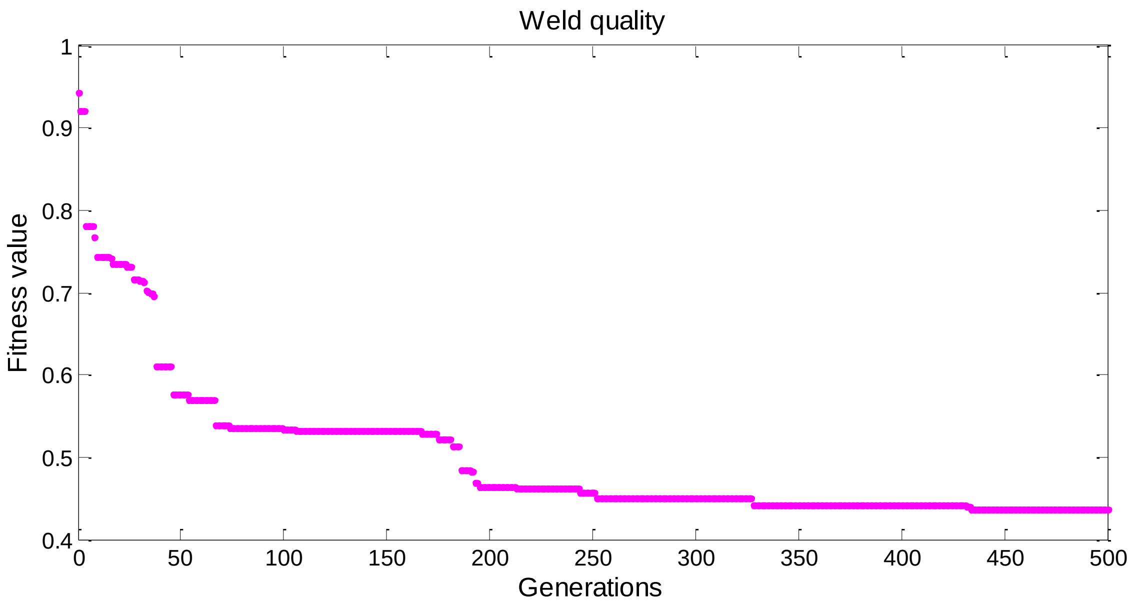

Figure 4.23 Fitness vs. Generations to optimise Weld quality of FSW with population size = 80. Elapsed time for training = 388.72 sec

4.5 Summary

Overall, in this Chapter, two major contributions were presented: (i) a NF model approach-based on spectral analysis and (ii) a GA-RBF optimisation which improves the performance of the models from previous simulations (Chapter 3) and maintains their simplicity and transparency.

In this Chapter, a NF model-based approach was successfully developed, allowing the deep analysis of the multiscale behaviour of the FSW process. The use of spectral-temporal analysis was proposed as the main vehicle to capture process information from bending forces. It was demonstrated how the tool bending forces measurements can be used to predict the final weld quality of the materials welded using FSW. Furthermore, the contribution of this spectral analysis can be extended to the potential reduction of the number of monitoring channels which are currently used to collect the bending forces information. This can lead to the development of simpler instrumentation of monitoring tools.

This is the first time that a spectral analysis has been used to capture indices related with the weld quality of the FSW process, and a NF model-based has been developed to evaluate the performance of the FSW. The spectral analysis may be used as a NDT. More importantly, the model based on spectral analysis of the bending forces may be used for real-time applications as this approach is computationally low.

The model presented shows good accuracy in the prediction of the weld quality of AA5083 aluminium alloys using 6mm thick sheets with the MX Tri-flute™ tool. It should be noted that it would be beneficial and useful to evaluate the performance of this technique in different materials and tool combinations. Moreover, it would be beneficial to perform more 'poor quality' welding trials to test the generalisation ability of the model, which is often a problem in data-driven modelling of FSW, as the current data consist of mostly good to average weld quality.

The aim of presenting a GA-RBF optimisation in this Chapter was to demonstrate that even with lack of data, the models previously developed can be improved by using hybrid techniques. The hybrid modelling technique proposed in this Chapter uses: (i) FCM to classify the data and create the rules which will describe the system; (ii) GA to search for optimum solutions and (iii) RBF to improve the learning process of the model. A clear enhancement of the multiscale models of the FSW process was summarised and presented in this Chapter. The knowledge acquired from the optimised models may serve as a basis for future studies in the area.

In general, the work presented in this Chapter, contributes to a deep understanding of the FSW from the perspective of force analysis. The simplification of the models via hybrid approaches can accurately describe complex behaviour of manufacturing processes at different scales. One of the main challenges in industry is, however, not only the collection and extraction of significant information, but also the identification of uncertain behaviour that can affect the process and how the system communicates this behaviour to the user. There is a lack of techniques which can accurately evaluate the prediction of models and present this information in human-reasoning context. The following Chapter will present a novel approach which has the ability to detect and evaluate new behaviour from the system in order to efficiently communicate the performance to the user.

5 A new ‘Novelty Detection’ framework based on fuzzy entropy with linguistic feedback

Overview

NF modelling has been extensively used to accurately describe and predict the behaviour of complex systems. However, one of the main challenges in CI-based modelling for complex manufacturing process is the interaction with humans. There is a need for developing models which can naturally interact and communicate unexpected behaviour from the systems. ND has been proposed as an approach which identifies new system dynamics that the model has not encountered before. There are several techniques based on ND which detect new process dynamics from data. Only a few of these approaches, however, deal with human reasoning which can lead to the natural interaction of machine-human. As presented in the literature review, FL systems are used to create models based on human reasoning. In this Chapter, a new ND framework is presented based on fuzzy entropy, a property of FL which is proposed as a measure of the quantity of information in a fuzzy set.

This Chapter presents a new ND framework which is created by taking advantage of the fuzzy entropy. The aim of this framework is to create a linguistic-based feedback mechanism which can advise the process users on the performance of complex manufacturing process. The main goals of the proposed framework can be listed as (i) warn the user when a new condition appears in the system, (ii) advise the user in regards to the reliability of the model's prediction when a novelty occurs.

The framework creates NF data-driven models, as discussed in previous Chapters, these models learn from complex dataset. The models in this Chapter are used to predict the quality of materials welded by FSW. During this investigation, the significance of predicting the quality of the welds produced by this welding technique was identified. It is very difficult to detect the generation of defects during the welding routine. This framework informs the performance of new behaviour in the system which can be linked to process variables affecting the quality of the joints.

The information presented regarding the performance of the system is given to the user in a simple sentence; this feedback concludes the human-centric concept of this novel framework. This Chapter starts with a brief introduction to the main CI concepts applied to develop the proposed framework: HCS, fuzzy systems and ND, later, the main contribution of this Chapter is presented. The methodology to create this framework based on fuzzy entropy is explained in detail. Finally, the results of this framework are applied to FSW. The models presented predict the weld quality of the system, and more importantly, provide linguistic feedback to the user from three different data sources: Experimental data, real-time data recorded in a single weld and synthetic data. The latter was evaluated to demonstrate the potential of this framework for real-time applications.

5.1 Fuzzy systems and novelty detection, a human-centric approach

One of the challenges in HCS is to design systems which can interact with humans by using simple and transparent features. Hybrid NF modelling techniques address this challenge by taking advantage of the interpretability features of FL systems, while maintaining a very good learning ability via the neural-network computational structure. The NF models have a simple structure. They are easy to understand (by the process users) and have the ability to not only process complex information, but also adapt and learn from the environment (data-driven supervised learning). As presented in the literature review, there are particular benefits of developing computational intelligent models based on neural networks and fuzzy systems: the relatively low computational cost and the good generalisation performance in describing complex nonlinear systems (Paiva and Dourado, 2004). A range of disciplines including engineering, healthcare and business informatics have taken advantage of such traits by developing intelligent systems based on NN and fuzzy systems approaches (Gupta, Jin, and Homma, 2003a). In manufacturing, several data-driven model-based approaches focused on NF modelling have been proposed to describe nonlinear mappings of complex industrial data (Elangovan et al., 2009; G. Panoutsos, Mahfouf, Beamish, and Norris, 2010; Zhang et al., 2011). Although models are used to accurately describe and even predict the behaviour of complex systems, the communication with human operators is often not intuitive, for example, when computational models need to communicate unexpected behaviour from the system (i.e., novelty detection).

In this Chapter, an ND framework, data-driven model-based, is proposed (Figure 5.1) to monitor the FSW process conditions, predict the performance of the process, and communicate to the user any new/unexpected system behaviour via a linguistic feedback mechanism.

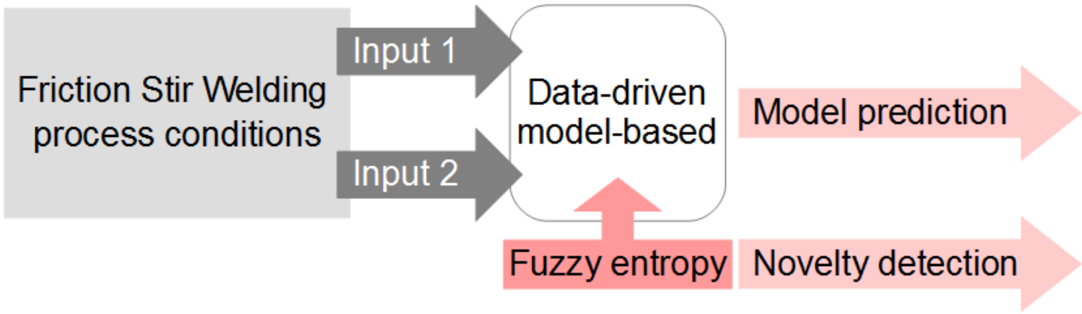

Figure 5.1 Data-driven model-based on novelty detection for FSW

5.2 A Novelty detection approach based on fuzzy entropy

5.2.1 Radial basis function and neural-fuzzy systems

As previously introduced in Chapter 2, Section 2.4.1, RBF is a powerful artificial NN used for learning complex input-output mappings (Gupta et al., 2003b). The RBF structure (see Figure 5.2) is commonly used with FL to model complex systems when there is a need for inherent system transparency and interpretability. This NN is a multidimensional nonlinear function mapping that can use data to learn input-output non-linear relationships.

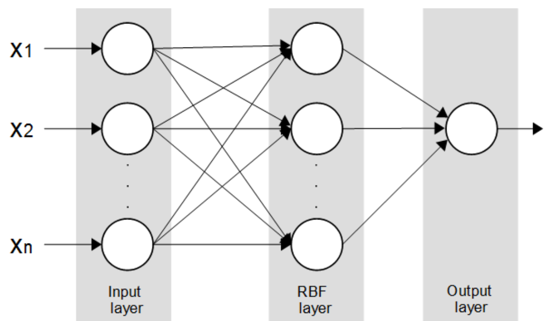

Figure 5.2 RBF neural network structure

One advantage of combining RBF neural networks with fuzzy systems is that linguistic fuzzy IF-THEN rules, which are naturally related to fuzzy membership functions, can be mathematically described in the model as a Gaussian radial basis function (L. X. Wang and Mendel, 1992). It thus provides a degree of inherent linguistic interpretability.

Consider a fuzzy system with inputs $x \in \Re^n$, M IF-THEN rules, the membership function $\mu_{A_i^j}$ for the jth rule $(j = 1,2,\dots,M)$, and the ith component (x_i) of the input vector x. If a singleton fuzzifier is used, the summative result of the jth rule on the input vector (x) is given by $(u_i(x) = \prod_{i=1}^{n} \mu_{A_i^j}(x_i))$, where $u_i(x) = \mu_{A_1^j}(x_1)\mu_{A_2^j}(x_2) \dots \mu_{A_n^j}(x_n)$.

As demonstrated in (Gupta et al., 2003a), the input-output equation of a fuzzy system with a singleton fuzzifier, product inference, and centroid defuzzifier can be expressed as:

$$\boldsymbol{y = \sum_{j=1}^{M} w_j \left(\prod_{i=1}^{n} \mu_{A_i^j}(x_i) \right)} \qquad \mathbf{(5.1)}$$

Where $w_j \in \Re^n$ $(j = 1,2,\dots,M)$ are the weight parameters, since the membership functions are nonlinear parameterised functions. Equation 5.1 represents a nonlinear neural network with a non-fuzzy input vector x, with membership functions (MFs) $\mu_{A_i^j}(x_i)$, weights w_j, and the nonfuzzy output $y \in \Re$.

There are several possibilities for the choice of a basis function. One of which are Gaussian networks. They are highly nonlinear and provide good locality for incremental learning (Gupta et al., 2003b). Here a Gaussian radial basis function is chosen as the membership function, consequently:

$$\boldsymbol{\mu_{A_i^j}(x_i) = exp\left(-\frac{1}{2} \sum_{i=1}^{n} \left(\frac{x_i - c_{ij}}{\sigma_{ij}} \right)^2 \right)} \qquad \mathbf{(5.2)}$$

When Equation 5.2 is used, Equation 5.1 can be rewritten as follows:

$$\boldsymbol{y} = \sum_{j=1}^{M} \boldsymbol{w_j} \left(\prod_{i=1}^{n} \boldsymbol{exp}\left(-\frac{\mathbf{1}}{\mathbf{2}} \sum_{i=1}^{n} \left(\frac{\boldsymbol{x_i - c_{ij}}}{\boldsymbol{\sigma_{ij}}} \right)^2 \right) \right)$$

$$= \sum_{j=1}^{M} \boldsymbol{w_j}\ \boldsymbol{exp}\left(-\frac{\mathbf{1}}{\mathbf{2}} \sum_{i=1}^{n} \left(\frac{\boldsymbol{x_i - c_{ij}}}{\boldsymbol{\sigma_{ij}}} \right)^2 \right) \tag{5.3}$$

$$\boldsymbol{y} = \sum_{j=1}^{M} \boldsymbol{w_j}\ \boldsymbol{u_j} \tag{5.4}$$

Where

$$\boldsymbol{\mu_j} = \boldsymbol{exp}\left(-\frac{\mathbf{1}}{\mathbf{2}} \sum_{i=1}^{n} \left(\frac{\boldsymbol{x_i - c_{ij}}}{\boldsymbol{\sigma_{ij}}} \right)^2 \right) \tag{5.5}$$

The parameters c_{ij} and σ_{ij} associated with the Gaussian membership functions are to be determined by process data.

As reviewed in Section 2.4, the use of intelligent hybrid approaches combining RBF neural networks with learning algorithms such as FCM and GA is widely applied in data-driven modelling due to its capability and computational efficiency. They can represent the fuzzy rule-based knowledge through a self-adaptive process (Jantzen, 1998). The proposed model-based framework applies the FCM algorithm to initialise the RBF network structure (initial clustering for the estimation of the membership functions). Its parameters are subsequently optimised using a GA as introduced in Section 2.4.3.

One of the challenges of manufacturing systems is the identification and communication of unexpected process performance. This involves the identification of new behaviours that have not been previously encountered by the model, and the evaluation and communication of this behaviour to the user. In this Chapter, the ND framework addresses this challenge.

5.2.2 Novelty Detection

ND deals with the identification of new and/or unknown system dynamics which the computational system has not previously encountered. NN have been used to design effective ND techniques with the ability to identify and evaluate 'unseen' data. These approaches have been used extensively for industrial applications, especially to detect possible faults during the process and diagnose the performance of the system (Brotherton and Johnson, 2001; Li, Pont, and Barrie Jones, 2002; Surace and Worden, 1998). One of the advantages of these techniques when monitoring an industrial process is that its results can be used online as demonstrated in (Crook, Marshland, Hayes, and Nehmzow, 2002; Sohn, Worden, and Farrar, 2001); The use of ND techniques in relation with fuzzy systems is, however, limited (Chaghooshi, Fathi, and Kashef, 2012; Lee, Kim, Cheon, and Kim, 2005; Liangqun, Hongbing, and Xinbo, 2006), despite the user-centric features offered by such techniques.

5.2.3 Fuzzy entropy

Fuzzy entropy based on Shannon's function was proposed in (Luca and Termini, 1972) as a measure of the quantity of information in a fuzzy set (fuzziness). The authors propose this approach for fuzzy modelling as a potential tool to analyse the information. This information is received when the user has to make a decision and in pattern analysis to classify information described by Fuzzy Systems (Luca and Termini, 1972, 1974).

By using Shannon's definition of entropy (Shannon, 1948) in fuzzy systems, the fuzziness measure of a membership degree μ can be written as:

$$\boldsymbol{f(\mu) = -\mu \, ln \, \mu - (1 - \mu)} \qquad \boldsymbol{(5.6)}$$

Thus, a fuzzy entropy formula on a finite universal set $X = \{x_1, \dots, x_n\}$ is defined as:

$$\boldsymbol{H(A) = -K \sum_{i=1}^{n} [\mu_A(x_i) \, ln \, \mu_A(x_i) + (1 - \mu_A(x_i)) \, ln(1 - \mu_A(x_i))], K > 0} \qquad (5.7)$$

Where, H represents a type of fuzziness of the fuzzy set A and μ is the membership. The 'fuzziness' of a given information set can be used to aid the novelty detection in a computational system, this is demonstrated in the following Sections 5.3 and 5.4.

Friction stir welding

Recently, the use of NF modelling techniques to describe the performance of the FSW process and predict its behaviour was presented in (George Panoutsos and Mahfouf, 2010). As presented in the literature review (Section 2.5), the use of CI techniques has also been proposed as tools to develop applications that can monitor this process in real-time. In the following Section, the creation of an ND framework is presented. It serves to identify possible new conditions during the FSW process (in real-time) and provides feedback of any process dynamics back to the user in a linguistic format.

5.3 A Novelty detection framework based on fuzzy entropy

5.3.1 Novelty detection framework

In this Section, the ND framework based on fuzzy entropy is presented in detail; Figure 5.3 illustrates the overall methodology.

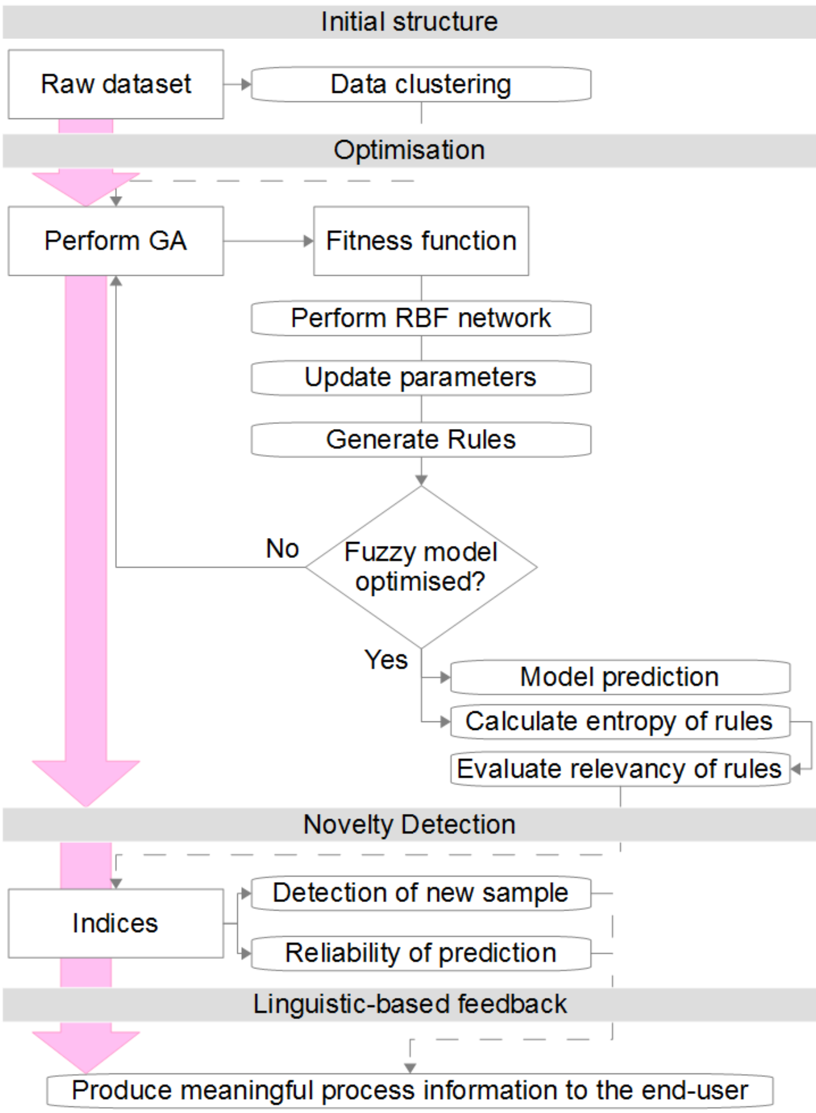

Figure 5.3 Flow chart of the novelty detection framework based on fuzzy entropy

5.4 Methodology

Initial structure

To generate the initial structure of the FL rule-base and assign the initial conditions for the optimisation of the model, the raw dataset is partitioned into multi-dimensional clusters of information using the FCM algorithm. This algorithm is frequently used in modelling approaches as a result of its ability to group and form clusters of data that have similar attributes. As shown in (Bezdek, 1981), by presenting a input-output dataset and assigning the number of clusters, the algorithm creates a list of optimal centres. With this information, the initial rule-base for the RBF neural network (centres (c), sigma (σ) and weights (ω) values) can be extracted as detailed in (Zhang and Mahfouf, 2007). For this framework, the number of clusters corresponds to the number of rules. The FCM methodology is used here as it conveniently creates FL membership clusters that can be used directly in the RBF system at low computational processing cost.

Optimisation

A genetic algorithm is used as an optimisation tool that searches for the optimum solution (rules and membership functions) for the RBF neural network structure given a training dataset (Table 5.2). The integration of GA, NN and fuzzy systems has been used to train and learn complex and non-linear input-output mappings. As discussed in the literature review, Section 2.4, the capability of RBF-NN and GA algorithm to analyse complex systems, learn from information, and seek accurate modelling structures has been successfully applied in previous studies (Linkens and Nyongesa, 1996). Several approaches have been proposed to optimise RBF neural networks using GAs. The optimisation presented in this Chapter is similar to the one shown in (Billings and Zheng, 1995), where the genes to build the chromosomes are defined based on the RBF network weights.

Using the information obtained from the initial structure, the variables to optimise (N_{vars}) and the chromosome can be defined, each chromosome is one fuzzy logic rule. The initial population ($InitPop$) is built as follows:

$p_1 = (c_1, \dots, c_r, \sigma_1, \dots, \sigma_r, \omega_1, \dots, \omega_r)\ r = number\ of\ rules,$

$chromosome = [p_1, \dots, p_{Nvars}]$

$InitPop = N_{pop} \times N_{vars}$

Where, N_{pop} is the population size, in this case, $N_{pop} = 30$.

The GA evaluates the fuzzy model structure by minimising the error between the desired output and the trained output. The fitness function is computed the Mean Square Error (MSE). During the evaluation of the fitness function, the GA generates possible solutions for the NN. Using Equation 5.4 the RBF computes the output of the system (y_{OUT}) and the resulting rules (denoted as M_{RULES}) are computed according to Equation 5.5.

When the termination criterion is achieved, the optimisation routine stops and the final output of the model and the fuzzy rules are obtained. At this stage, the fuzzy entropy of the optimised fuzzy rules is measured using Equation 5.7, this fuzzy entropy measurement ($H(M_{RULES})$) is the main contribution to create ND approach.

The optimisation of the RBF parameters includes the following steps:

Step 1: Initial structure, raw dataset is partitioned into n clusters using FCM. Centres (c), sigma (σ) and weights (ω) values are produced for the RBF neural network.

Step 2: Set $t = 1$. Randomly generate N solutions to form the first population, P_1. Evaluate the fitness of solutions in P_1. Using the information obtained from Step 1, the variables to optimise (N_{vars}) and the chromosome can be defined.

$p_1 = (c_1, \dots, c_r, \sigma_1, \dots, \sigma_r, \omega_1, \dots, \omega_r)\ r = number\ of\ rules,$

$chromosome = [p_1, \ldots, p_{Nvars}]$

$InitPop = N_{pop} \times N_{vars}$

N_{pop} is the population size, in this case, $N_{pop} = 30$.

Step 3: Crossover, Generate an offspring population Q_t as follows:

Choose two solutions x and y from P_t based on the fitness values.

Using a crossover operator generate offspring and add them to Q_t.

Step 4: Mutate each solution $x \in Q_t$ with a predefined mutation rate.

Step 5: Fitness assignment: Evaluate and assign a fitness value to each solution $x \in Q_t$ based on its objective function value. The fitness function is computed by minimising the error between the desired output ($RBF_{measured}$) and the trained output ($RBF_{predicted}$). Using Equation 5.4 the RBF computes the output of the system and the resulting rules (M_{RULES}) are computed according to Equation 5.5

Step 6: Selection: Select N solutions from Q_t based on their fitness and copy them to P_{t+1}.

Step 7: If the stopping criterion is satisfied, terminate the search and return to the current population, else, set $t = t + 1$ got to Step 3.

Step 8: When the termination criterion is achieved, the final output of the model and the fuzzy rules are extracted.

Step 9: The fuzzy entropy of the optimised fuzzy rules ($H(M_{RULES})$) is measured using Equation 5.7.

Novelty detection

The fuzzy entropy of the optimised rules ($H(M_{RULES})$) is the main component used to aid the creation of the ND approach. Figure 5.4 shows an overview of the applied methodology.

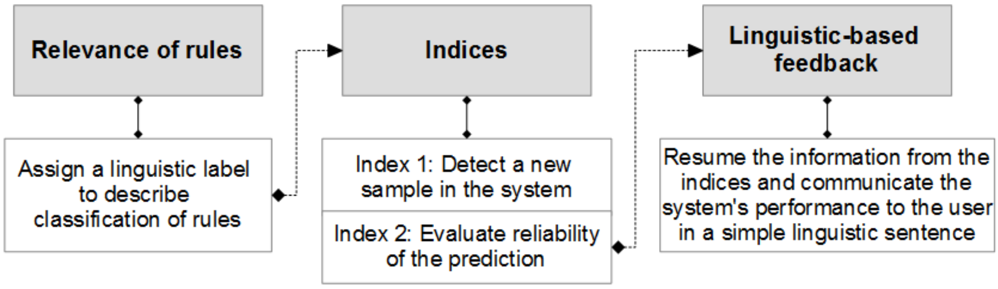

Figure 5.4 Overview of the novelty detection approach

a) *Relevance of rules:* At this stage of the algorithm, the rules which are relevant to a given data class are identified. For each data point (process measurement) presented to the system/model, the relevance of a given rule to a specific output class can be estimated by correlating the firing strength of each rule to each of the output classes. This process will result in a ranked list of rules ($Rule_{firing}$) which contribute to certain output classes. Each rule is then assigned a linguistic label ($LV_{CorrVal}$) which is subsequently used in the linguistic feedback provide to the user, as previously shown in Figure 5.4.

b) *Novelty Indices:* Using the fuzzy entropy $H(M_{RULES})$, two indices were created to evaluate the novelty of each data sample:

   i. **Index 1**. This monitors the entropy of the system and detects if new/unseen conditions are encountered in the system in real-time. The hypothesis predicts that a new data point, with different process dynamics to the ones included in the system, will trigger an entropy value (sum from all the fired rules) that identifies the 'new'. An upper boundary +1% (UBH) and lower boundary (LBH) -1% are set based on the minimum value ($MinV_{HR}$) of $H(M_{RULES})$ to then obtain a numerical index (ND) which determines if the current sample is a new condition or not. This process creates a binary decision on the novelty of the sample, and is produced as follows:

$$\boldsymbol{If\ MinV_{HR}\ is\ > UBH\ or < \ LBH\ then\ ND = 1} \qquad (\mathbf{5.8})$$

$$\boldsymbol{If\ MinV_{HR}\ is\ < UBH\ or > \ LBH\ then\ ND = 0} \qquad (\mathbf{5.9})$$

Where $ND = 0$ indicates that no new condition is present and $ND = 1$ indicates that a possible new condition is present in the system.

ii. **Index 2**. Measures the reliability of the prediction for each sample. Although, the first index (ND) is a criterion of data novelty, (ND) is based on the assumption that the rules are sufficiently reliable to extract such information. This is not always the case given the uncertainty of the training data. The normalised ratio of the entropy of a rule over the maximum presented entropy in the system is used a measure of how 'fuzzy', or relatively reliable, a rule is within the overall rule-base. This is calculated as follows:

$$\boldsymbol{PercV_{HR} = H(M_{RULES})/maximum\ value\big(H(M_{RULES})\big) * 100} \qquad (\mathbf{5.10})$$

The scope of the above indices is, to extract the following information in real-time: (i) to identify samples with relatively 'new' dynamics/behaviour and (ii) for each sample to estimate how reliable the predicted output is. This information is summarised in a linguistic feedback mechanism that is returned to the process user as a form of decision support.

Linguistic-based feedback

Using the information from the indices previously described, a knowledge-structure is created by assigning numerical and linguistic hedges to the system's variables: *'sample value'* is a numerical variable that describes the sample evaluated; *'rule label'* is a linguistic label that describes the classification of the rules; *'prediction value'* is the output predicted for the sample evaluated (numerical variable), and '*reliability label*' is a linguistic label related with the reliability measurement. '*WQ*' is a linguistic variable that describes the output of the system. The performance of the system is summarised as follows:

Table 5.1 Linguistic-based knowledge structure

System variables	*Values*	*Linguistic hedges*
Sample No	*sample value*	
Index 1: Novelty detection (Equations 5.8 and 5.9)	*ND*	ND = 0 'Not new', ND = 1 'New' (sample is a 'New'/'Not new' condition
Index 2: Reliability (Equation 5.10)	$PercV_{HR}$	For the $Rule_{firing}$ prediction is associated with: $LV_{CorrVal}$ (*rule label*)
Output predicted (Equation 5.4)	*prediction value*	For WQ = *prediction value*, reliability of prediction is *reliability label*

From the information in Table 5.1, a linguistic-based feedback is created and presented to the user as a simple sentence:

"Sample 'sample value' is a 'new' / 'not new' condition, with a system predicted output of WQ = 'prediction value'. The most relevant rule in the system relates to 'rule label' weld quality, and this prediction is of 'reliability label' reliability".

Novelty
Prediction
Reliability
Relevance of rule

The demonstration of the ND framework is shown in the following Section.

5.5 A new novelty detection framework and its application to FSW

A dataset of 34 weld samples was used to simulate the ND framework. The model simulation was produced using two inputs (tool rotational speed, traverse speed) and one output (weld quality), 70% of the data samples were used for training, and

30% for testing (Table 5.2). The weld samples were obtained by welding plates of AA5083 aluminium alloy (6mm thick) at different process conditions: tool rotational speed (from 280 RPM to 580 RPM), and traverse speed (between 280 mm/min to 812 mm/min).

Table 5.2 Training and testing dataset used to create the ND framework for FSW

	Weld Sample	Tool Rotational Speed (RPM)	Traverse Speed (mm/min)	Weld Quality (WQ)
TRAINING DATA	1	280	168	0
	2	280	224	0
	3	280	336	0
	4	280	392	2
	5	355	213	1
	6	355	284	0
	7	355	426	0
	8	355	497	1
	9	380	304	0
	10	380	304	0
	11	380	304	2
	12	380	304	0
	13	380	456	0
	14	380	532	1
	15	380	608	2
	16	380	684	3
	17	430	258	0
	18	430	344	0
	19	430	516	1
	20	430	602	1
	21	505	303	0
	22	505	404	0
	23	505	606	0
	24	505	707	2
	25	580	348	2
	26	580	464	2
	27	580	696	5
	28	580	812	8
TESTING DATA	1	280	280	0
	2	355	355	0
	3	380	304	2
	4	430	430	0
	5	505	505	1
	6	580	580	1

The resulting simulations exhibited good system performance in the prediction of the weld quality as shown in Figure 5.5. The performance measured for training was 0.411 and 0.986 for testing.

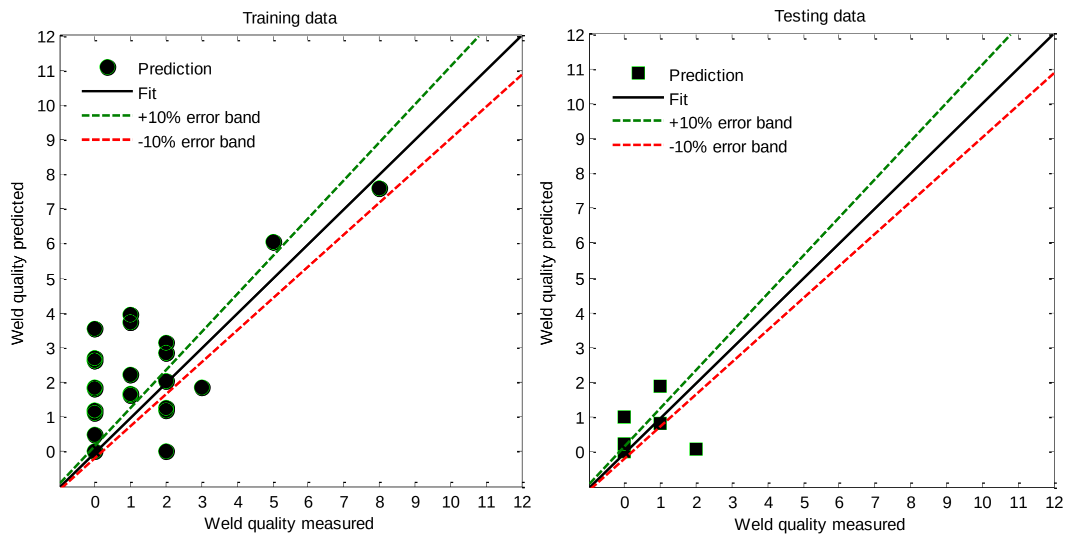

Figure 5.5 Weld quality training and testing performances

The quality of the welded samples was quantified by process experts, using four different indices: bend test-root, bend test-face, surface finish and cross sectional inspection (to identify internal flaws). Each index was expressed in a numerical value between 0 – 3 using expert knowledge:

A final summative index was then created by aggregating the four sub-indices: 'Weld Quality' (WQ) and it results in a range between 0 – 12, where 0 = 'Good WQ' and 12 = 'Poor WQ'.

Figure 5.6 shows the correlation of the rules with the weld quality of the system and the relevance of rules per sample. The rules were analysed using Pearson's coefficient (MathWorks, 2011; Nandagopalan, 1994; Pearson, 1895) as correlation approach in order to establish the one-to-one relationship of the rules as compared to the weld quality of the process. Based on the correlation results in Table 5.3, Rules R2 and R3 are rules related to 'Good WQ', R1 and R5 are rules related with 'Poor WQ'. The relevance of the rules to the weld quality is estimated by assessing which rules are 'fired' for each data sample, and also the relevant firing strength. This is achieved via the calculation of the Fuzzy Entropy (Equation 5.7).

Table 5.3 Relation of rules with WQ

Rule	Pearson's correlation value	Relation with WQ
R1	0.75	Poor
R2	-0.48	Good
R3	-0.21	Good
R4	0.13	Neutral
R5	0.86	Poor

For example, the correlation between the relevancy of rules and the WQ can be described as follows: out of the five rules (R1-R5), for sample No. 28, the rule firing the highest is R1 which is related with 'Poor WQ' (Figure 5.6).

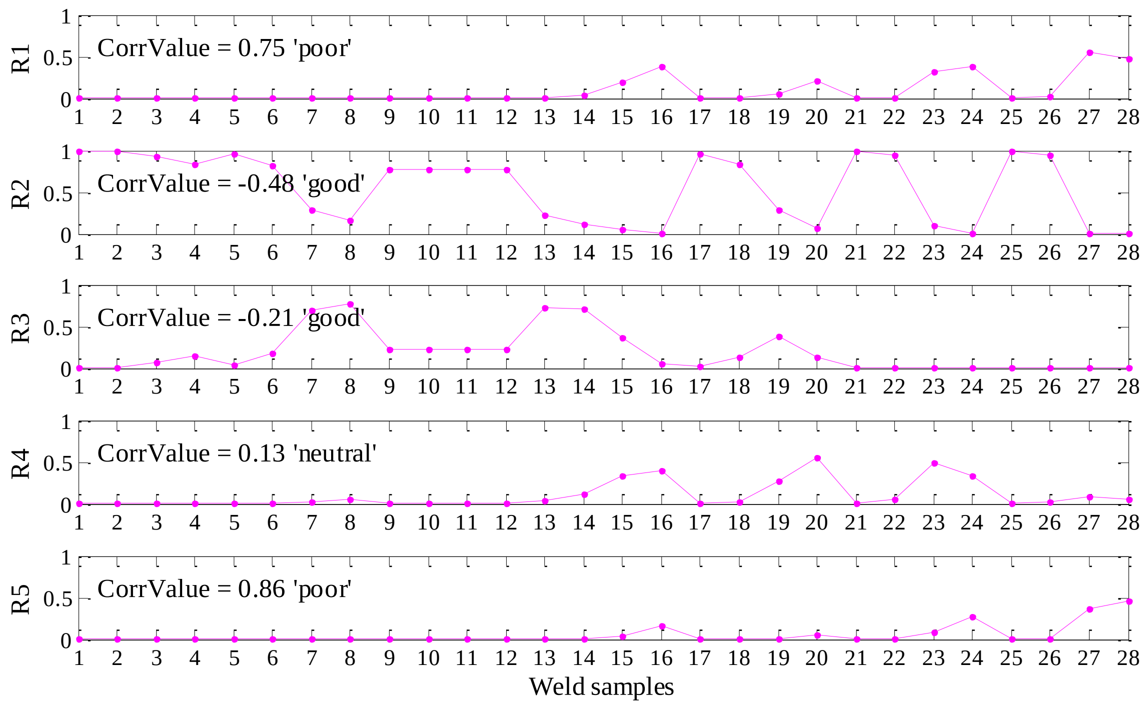

Figure 5.6 Relevance of rules and relation with WQ (y-axis represent the Fuzzy Entropy)

The ND framework was evaluated with testing data from three different sources: Experimental data (Figure 5.7) and real-time data pre-recorded in a single weld (Figure 5.8), the real-time dataset was also evaluated using synthetic process data

(Figure 5.9) the aim is to demonstrate the potential of this ND approach towards real-time applications.

5.5.1 Experimental results and simulations

The ND indices are calculated for a number of process samples and these are shown in Figure 5.7. The average entropy value of the rule-base is shown in Figure 5.7 (a) for the experimental testing dataset. The novelty detection index (Index 1) is calculated per sample according to the rule described in Equation 5.8 and Equation 5.9. For the dataset samples 2, 4, 5 and 6, it was detected that new conditions occur.

Figure 5.7 (b) shows the most relevant rule associated with each prediction for each sample, along with the linguistic reliability indicator for that rule. For example, in the samples 1, 2, 3 and 4, rule 2 (R2) is the most relevant rule to the corresponding prediction and this rule is also related with 'Good WQ' (as shown previously in Figure 5.6). The rules in samples 5 and 6 (R5 and R1) are related with 'Poor WQ'. In each case, the reliability of the weld quality prediction for each sample is described by the linguistic label associated with the rule.

Figure 5.7 (a) and Figure 5.7 (b) show the relationship of the entropy calculation and the prediction of the reliability of each rule. For example, for each weld sample the average Fuzzy Entropy of all rules is calculated, and this information is used to assess the reliability of the prediction for this particular weld sample (noted on Figure 5.7 (b)). Depending on the % outcome of Equation 5.10, the linguistic variables for the reliability measurements are described in Table 5.4.

Table 5.4 Linguistic interpretation of reliability

% Value	Linguistic interpretation	Linguistic value
0%-25%	Low reliability	'L'
26%-50%	Medium-Low reliability	'ML'
51%-75%	Medium-High reliability	'MH'
>76%-100%	High reliability	'H'

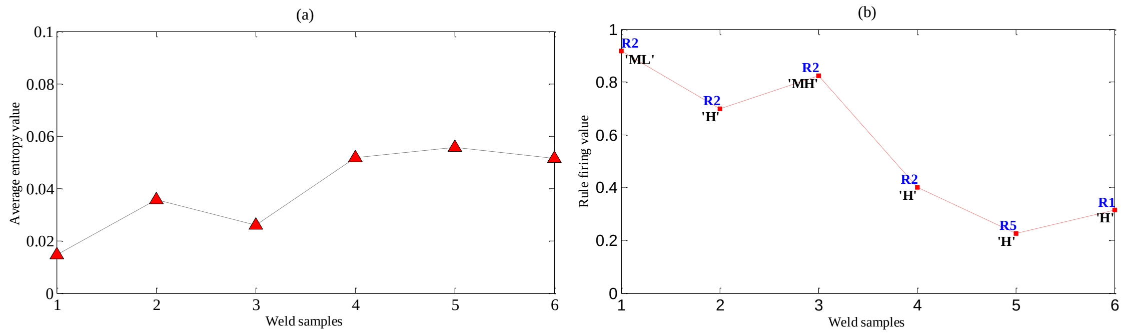

Figure 5.7 ND performance of the experimental testing dataset: (a) monitoring the entropy, (b) relevance of rules and reliability of prediction

To summarise the information concerning the ND performance, a linguistic-based knowledge structure is created. Table 5.5 illustrates an example for the case of sample 4.

Table 5.5 A linguistic-based knowledge structure for experimental testing dataset

System variables	*Values*	*Linguistic hedges*
Sample No	4	
Index 1	1	ND = 1; sample is a 'New Condition'
Index 2	R2	Index 2 = R2 then prediction is related with 'Good' WQ
Output predicted	0	For WQ = 0, reliability of prediction is 'High'

Based on this data set, a linguistic-based feedback on the ND is presented to the user in a simple sentence formed as follows:

"Sample 4 is a New condition,

with a system predicted output of WQ = 0.

The most relevant rule in the system relates to Good weld quality,

and this prediction is of High reliability"

For the second experiment, the model was presented with a dataset recorded in real-time for a single weld. The process conditions of the system were evaluated every 30 seconds. The results are shown in (Figure 5.8), as in the first example,

Figure 5.8 (a) shows the average entropy value for the real-time dataset and Figure 5.8 (b) presents the values of Index 2 per sample.

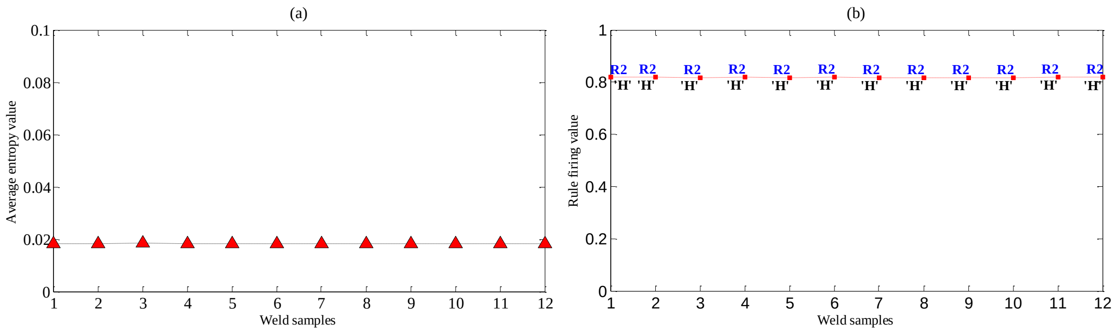

Figure 5.8 ND performance of the pre-recorded real-time dataset: (a) monitoring the entropy, (b) relevance of rules and reliability of prediction

The linguistic-based knowledge structure for sample 6 is created as follows:

Table 5.6 A linguistic-based knowledge structure for pre-recorded real-time dataset

System variables	*Values*	*Linguistic hedges*
Sample No	6	
Index 1	0	ND = 0; sample is a 'Not New Condition'
Index 2	R2	Index 2 = R2 then prediction is related with 'Good' WQ
Output predicted	0	For WQ = 0, reliability of prediction is 'High'

"Sample 6 is a Not new condition,

with a system predicted output of WQ = 0.

The most relevant rule in the system relates to Good weld quality,

and this prediction is of High reliability"

Finally, for the third experiment, the synthetic dataset was presented to the model with 20% of weld samples altered from the normal process conditions. The results are shown in Figure 5.9. As in the previous example, Figure 5.9 (a) shows the average entropy value for the synthetic dataset and Figure 5.9 (b) presents the values of Index 2 per sample.

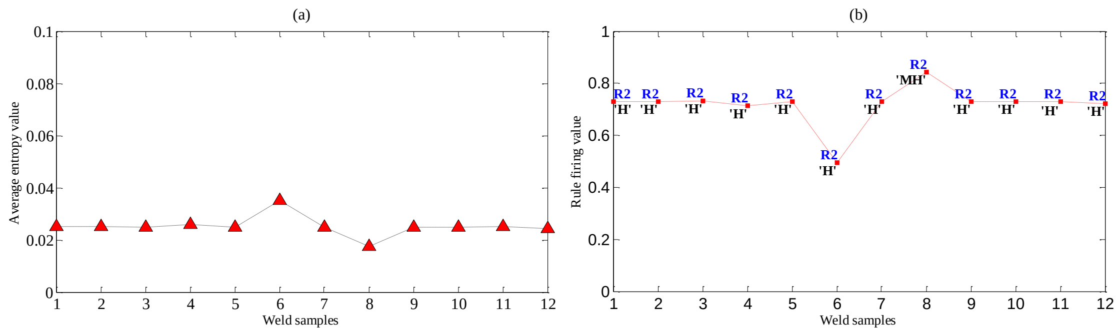

Figure 5.9 ND performance of the synthetic dataset: (a) monitoring the entropy, (b) relevance of rules and reliability of prediction

The new data samples (6 and 8) are correctly identified by the system as 'new' conditions. The knowledge structure extracted from the model and the linguistic feedback are shown below for sample number 8:

Table 5.7 A linguistic-based knowledge structure for pre-recorded synthetic dataset

System variables	*Values*	*Linguistic hedges*
Sample No	8	
Index 1	1	ND = 1; sample is a 'New' condition
Index 2	R2	Index 2 = R2 then prediction is related with 'Good' WQ
Output predicted	2	For WQ = 2, reliability of prediction is 'Medium-High'

"Sample 8 is a New condition,

with a system predicted output of WQ = 2.

The most relevant rule in the system relates to Good weld quality,

and this prediction is of Medium-High reliability"

These experiments have demonstrated that the linguistic feedback is an efficient and simple mechanism. It can provide meaningful process information to end-users by taking advantage of the computational elements of FL systems, including simple and transparent models; the framework is computationally inexpensive which can lead to the development of real-time applications.

5.6 Summary

There is a clear need for developing intelligent models that can communicate with humans in a natural way. For manufacturing processes it is crucial to implement HCS which can communicate unexpected behaviour and can accurately evaluate the performance of the system. ND was proposed in this Chapter to address these challenges. Fuzzy entropy was used as an effective ND approach as it identifies information that the system has previously not seen. A new framework based on fuzzy entropy which makes use of a model-based approach to identify new process conditions was created. The fuzzy entropy proposed is based on Shannon's entropy. An NF modelling structure was used to develop the core knowledge of the system, while an FCM algorithm along with a GA were used to optimise the system's structure and parameters.

Several contributions were presented in this Chapter: namely, the benefits of the use of fuzzy entropy to measure information in data were demonstrated, as well as the linguistic interpretability of the FL systems to create an HCS capable of providing feedback to the user via linguistic information. The proposed framework based on HCS presents information regarding the system's performance and detects new behaviour. Furthermore, the feedback presented is summarised in simple sentences which can communicate naturally with the user.

The framework was successfully applied for FSW in order to study its complex and non-linear process conditions and predict the weld quality of the materials welded using this technique. This framework was applied for the first time to investigate experimental, real and artificial datasets which evaluate the quality of the material. The results of these experiments, demonstrated the linguistic feedback of the system for the three industrial-based scenarios. Furthermore, the system's computational efficiency allows it to run in real time. This was demonstrated in the artificial data experiments. Another contribution in this Chapter is the ability of this framework for potential applications in real-time. The framework was tested with pre-recorded real-time data. The results were produced in less than two seconds, assuming that a welding routine takes between one to four minutes, the proposed framework has the potential to be used as an autonomous/semi-autonomous system for monitoring complex manufacturing processes in real-time while, also providing linguistic feedback to experts and non-experts.

So far, the models presented in this investigation, have demonstrated the ability of CI modelling techniques to accurately predict the performance of complex industrial processes using only two inputs and one output. Mechanical properties, microstructure and quality of the welds have been successfully modelled. Potential applications for online techniques have been proposed in this thesis. The experiments so far presented are encouraging to use these CI models to monitor and evaluate industrial processes in real-time. Nevertheless, many industrial processes required the evaluation of not only one solution (output) but multiple solutions which are inter-connected which each other. The CI models developed so far have been optimised to find a single solution. However, due to the multiscale nature of FSW and most real-world problems, it is necessary to use approaches which can simultaneously optimise various solutions. Multi-Objective optimisation is proposed in this investigation to address this issue. Its ability to map relationship and find multiple solutions of complex systems such as FSW is demonstrated in the next Chapter.

6 Real-time Multi-Objective Optimisation of Process Operating Windows for Friction Stir Welding

Overview

Optimisation usually refers to finding one or more feasible solutions which correspond to optimal values of one or more objectives. The need for finding such optimal solutions in a problem comes mostly from the extreme purpose of either designing a solution for minimum possible cost of fabrication, or for maximum possible reliability (Deb, 2001). The models so far presented have demonstrated the effectiveness of CI modelling techniques to optimise, predict and evaluate the performance of a complex manufacturing process. The approaches presented in previous Chapters are suited for real-time applications to optimise single-objective problems. However, many manufacturing processes and real-world problems demand simultaneous optimisation of various solutions. For this reason, multi-objective optimisation, based on evolutionary algorithms, is proposed in this investigation. Multi-objective optimisation is proposed for either designing a solution for minimum possible cost of fabrication, or for maximum possible reliability or quality. Evolutionary algorithms such a GA mimic nature's evolutionary principles to guide their search towards optimal solutions. Nowadays optimisation methods are of significant importance particularly in engineering design, scientific experiments and decision-making (Deb, 2001; A. Mukhopadhyay et al., 2014; Anirban Mukhopadhyay et al., 2014).

It is worth mentioning that for manufacturing applications, process experts often wish to determine the minimum or maximum values of the input process parameters at which the responses can reach their optimum. The design of systems which can find the optimal design for a set of given inputs (process parameters) allows insights into the underlying processes on their various scales. In this chapter, a multi-objective optimisation of the created NF models was proposed for the first time to find optimal solutions which can help the user to optimal design of FSW. The multi-objective optimisation is based on micro-GA which is proposed to considerably reduce the computational cost of this algorithm. The novel multi-objective optimisation framework presented in this Chapter, is highly suitable for real-time applications. This framework is applied to study the multiscale behaviour of FSW; its application is also useful for finding the optimal POW of this complex process for the analysis of two trade-off properties.

This Chapter begins by presenting the background of multi-objective optimisation and the GA and micro-GA Evolutionary Algorithms. The hybrid approaches used in this Chapter are briefly reviewed. NN are used in this Chapter within the optimisation routine, RBF is proposed not only for the optimisation of the solutions but also, its learning ability is used from previous NF models.

A brief review of investigations that have used and developed hybrid multi-objective optimisation for manufacturing process is presented. Then, the early stage of the optimisation framework for the design of manufacturing process is presented and the results for single-objective optimisations are discussed. It is important to demonstrate how the single-objective problem leads to the development of a more advanced framework for multi-objective problems. Based on preliminary results obtained for a single-objective problem, the optimisation was extended to find multiple solutions of two variables. It is demonstrated that the proposed approach is computationally inexpensive and suited to optimise multiple solutions of complex manufacturing processes such as FSW. Finally, the results of this real-time approach are presented. Six models which describe the multiscale behaviour of FSW were evaluated and encouraging results were obtained. This is the first time in this area that a multi-objective framework was applied to find the optimal speeds which satisfied certain requirements from the user for the various scales of the FSW such as specific mechanical properties, microstructure and quality of the welds.

6.1 Multi-objective optimisation using hybrid CI-based paradigms

Multi-objective optimisation and genetic algorithms

GA are population-based evolutionary systems with the ability to solve single-objective and multi-objective optimisation problems. A single-objective GA can be modified to find a set of multiple non-dominated solutions. The ability of GA to simultaneously search different regions of a solution space makes it possible to find a diverse set of solutions for difficult problems. As reported by Jones et al (Jones, Mirrazavi, and Tamiz, 2002), GA have been the most popular approach to multi-objective design and optimisation problems.

As most real-world problems are multi-objective (i.e., solutions are in conflict with each other), many engineering problems require minimize costs while maximising performance (Konak, Coit, and Smith, 2006). The use of multi-objective optimisation is therefore proposed in this investigation.

Multi-objective optimisation involves the minimization or maximization of more than one objective function. The general multi-objective optimisation problem can be formally defined as:

Find the vector $\vec{x}^* = [x_1^*, x_2^*, \dots, x_n^*]^T$ which will satisfy the m inequality constraints (Coello Coello, 2001): $g_i(\vec{x}) \geq 0 \quad i = 1,2, \dots, m$, with the p equality constraints $h_i(\vec{x}) = 0 \quad i = 1, 2, \dots, p$, and will optimise the vector function: $\vec{f}(\vec{x}) = [f_1(\vec{x}), f_2(\vec{x}), \dots, f_k(\vec{x})\ ]^T$. Where k is the number of objective functions and x is the vector of n decision variables that represent a solution in the feasible space.

In many multi-objective optimisation problems, the objective functions are usually in conflict with each other. Therefore, it is not possible to obtain a solution that minimises each objective function concurrently. One answer for these problems consists of a set of solutions called Pareto optimal. But, prior to defining Pareto optimal, the concept of dominant must be introduced. Assume that x_1 and x_2 are vectors in n-dimensional space and f is a function, x_1 dominates x_2 if the following conditions are satisfied:

$$\begin{cases} \boldsymbol{f_i(x_1) \leq f_i(x_2)} & (\forall_{\boldsymbol{i}} = \boldsymbol{1}, \dots, \boldsymbol{k}) \\ \qquad\qquad \boldsymbol{and} & \\ \boldsymbol{f_i(x_1) < f_i(x_2)} & (\exists_{\boldsymbol{i}} = \boldsymbol{1}, \dots, \boldsymbol{k}) \end{cases} \tag{6.1}$$

Pareto optimal is a solution which is not dominated by any other solution in the solution space. Pareto optimal solution cannot be improved with respect to an objective unless at least another objective is deteriorated. A series of all these non-dominated solutions is called Pareto optimal set, and the objective function values in the objective space are the Pareto front. The major goal in multi-objective optimisation is to find the Pareto front, which consists of Pareto optimum solutions (Deb, 2001).

The first multi-objective GA, known as VEGA was proposed by (Schaffer, 1985). Since then, several multi-objective algorithms based on evolutionary algorithms have been developed. In (Deb, 2001), Deb presents an exhaustive analysis of the most widely known algorithms. He introduces the background, describes the theory, and analyses the advantages and disadvantages of each algorithm. In this Chapter, the use of micro-GA is proposed to create a multi-objective optimisation framework which is suitable for real-time applications.

Micro-GA

A micro-GA is a genetic algorithm which uses a very small population and a routine which continuously generates genetic diversity throughout generations (Alvarez, 2012; Coello and Pulido, 2001a). The idea of using small populations was first suggested by Goldberg (Goldberg E., 1989), he reported that by using a population size of only 3, enough converge could be achieved. The first micro-GA algorithm was implemented by (Krishnakumar, 1989), he used a population size of 5, a crossover rate of 1, a mutation rate of zero and an elitist strategy which copies the best string found in the current population to the next generation, and the selection process was created by declaring as a winner the individual with the highest fitness. The author compared his approach with a classic GA. He reported faster and better results when using a micro-GA for single-objective optimisation. As a result, a micro-GA for multi-objective optimisation was proposed first by (Coello and Pulido, 2001a). This algorithm uses two memories: (i) as a source to maintain the diversity and (ii) to achieve members of the Pareto optimal set. The population is operated in a similar way to that of the single-objective micro-GA. The authors compared this micro-GA multi-objective approach with NSGA-II. The multi-objective micro-GA exhibited a lower computational cost than NSGA II. An approach which applies a micro-GA for single-optimisation problems is presented by (Liu, Lin, Shi, and Teng, 2011), the study shows the effectiveness of micro-GA for the design of mechanical problems.

It is worth mentioning that little literature was found regarding the use of micro-GA for multi-objective optimisation problems, especially for real-time applications.

Radial basis function neural network for optimal design of FSW

As previously discussed in the literature review (Section 2.4) and demonstrated in the previous Chapters, RBF neural networks are proposed in this thesis, because of their transparency and learning abilities. One of the advantages of using RBF for modelling approaches is their adaptability when combined with fuzzy systems and GA. RBF have been widely used to create hybrid models that are computationally efficient and transparent (M. Y. Chen and Linkens, 2001; Hong et al., 2001; Pedrycz and Gomide, 2007a; Sánchez et al., 2010). RBF have successfully been used to deal with multi-objective problems, as presented in (Santana-Quintero, Serrano-Hernández, Coello, Hernandez-Diaz, and Molina, 2007) a hybrid approach based Gaussian RBF and rough sets theory was applied for several functions and the results were compared against NSGA-II. This approach suggests the use of these hybrid multi-objective algorithms for real-time applications.

In this Chapter, the knowledge acquired from previous NF models is used to create hybrid models which are able to use little information from the system and design the optimal solutions for manufacturing processes, in this case for FSW. The previously calculated centres (c), sigma (σ), and weights (ω) values from each one of the NF models presented in Chapter 4 are used to estimate the output of the system based on the user settings. The RBF neural network structure is used as follows:

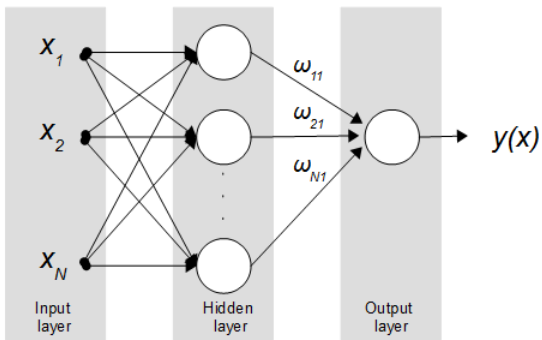

Figure 6.1 RBF neural network structure

In this investigation, the Gaussian function was chosen as the active function of the hidden layer nodes of the RBF.

$$\boldsymbol{\varphi_l(x) = exp\left[-\frac{\|x - c_l\|^2}{\sigma_l^2}\right]; \qquad l = 1, \dots, L} \qquad (6.2)$$

Where x is an n-dimensional input vector, c_l is the centre of the Gaussian function, L is the number of nodes in the hidden layer, and σ_l is the width of the Gaussian function. The output of each node is computed as:

$$\boldsymbol{y_j(x) = \sum_{l=1}^{L} \omega_l \varphi_l(x)} \qquad (6.3)$$

Where ω_l denotes the weight between the j^{th} output and the l^{th} node in the hidden layer.

6.2 Multi-objective optimisation for manufacturing applications

Many manufacturing systems involve multiple conflicting measures of performance, or objectives, which need to be optimised simultaneously. A recent two part reviews of multi-objective evolutionary algorithms for data mining approaches is presented in (A. Mukhopadhyay et al., 2014; Anirban Mukhopadhyay et al., 2014). These reviews reflect the use of approaches such as Fuzzy Systems, NN, and clustering techniques to create more advanced and efficient applications of multi-objective algorithms for real-life problems.

In the last decade, multi-objective optimisation techniques based on intelligent modelling have been applied for the design of materials and specially alloys of different metals. For instance, (Zhang and Mahfouf, 2010, 2011) developed multi-objective optimisation mechanisms to design the optimal microstructure and predict mechanical properties of alloy steels using bio-inspired algorithms, evolutionary algorithms and data-driven approaches. Their approaches, find the best parameters (i.e. chemical composites) that satisfy the requirements for specific mechanical properties of steels (ROA, UTS). Another examples of multi-objective algorithms applied to the design manufacturing processes was presented by (A R Yildiz and Ozturk, 2006), their hybrid approach, which consisted of GA and Taguchi methods, was applied to optimise tuning operation for the determination of cutting parameters considering minimum cost and a set of machining constraints. An extensive review of multi-objective evolutionary algorithms for aeronautical and aerospace engineering optimisation and design problems is given by (Arias-Montano, Coello, and Mezura-Montes, 2012), among other issues, the authors pointed out the lack of approaches using micro-GA despite successful applications in this area (Szőllős, Šmíd, and Hájek, 2009). Another challenge which is highlighted in this study is the need of applying multi-objective approaches for complex physical simulations to improve or avoid the use of CFD techniques which are computationally expensive. ANN (Chandrasekaran, Muralidhar, Krishna, and Dixit, 2010), NF systems (Gama and Mahfouf, 2009) and other evolutionary algorithms such as particle swarm optimisation (A. R. Yildiz, 2012) have been proposed to design and optimise industrial processes.

More recently, investigations regarding the optimisation of multiple parameters and optimal design of FSW have been proposed. For example, in (PERIYASAMY, MOHAN, BALASUBRAMANIAN, RAJAKUMAR, and VENUGOPAL, 2013), a multi-objective optimisation of FSW parameters was proposed using Response Surface Methodology (RSM) to optimise the FSW parameters and obtain the maximum tensile strength and weld nugget of the joints. A different approach which uses particle swarm optimisation was presented by (Shojaeefard, Behnagh, Akbari, Givi, and Farhani, 2013), where the Pareto optimal set of solutions to predict the UTS and hardness of aluminium alloys AA7075-AA5083 was obtained as functions of weld and rotational speeds. Another recent approach which aims the optimal design of FSW using artificial NN was presented by (Chiteka, 2014), the author presents to the system UTS information to obtain the possible optimal speeds.

However, as the author states, this technique is computationally expensive due to the multiple combinations of speeds which form a more complex hidden layer, the author also highlights that the training information could be improved if more experimental data is available. Most of the approaches dedicated to optimise FSW (for single or multiple problems) do not address the use of these approaches for real-time applications.

6.3 Optimal design of FSW for a single-objective problem

This Section presents the preliminary results which lead to the development of a real-time multi-objective optimisation framework which is presented later in this Chapter. In this Section, detailed information regarding to the use of knowledge generated from the models created in Chapter 4 is presented. The knowledge used for this optimisation is related with the centres (c), sigma (σ), and weight (ω) values generated from the training data during the RBF evaluation. In Chapter 4, two inputs were used to predict one output; the RBF then was used to find the optimal values of c, σ, and ω used to create the NF models.

In this section, the RBF is used as a fitness function to find the optimal solutions based on a given settings. In this case, the optimal solutions are the tool rotational speed and traverse and the given settings are the properties desired. The GA implemented for a single-solution is illustrated in Figure 6.2.

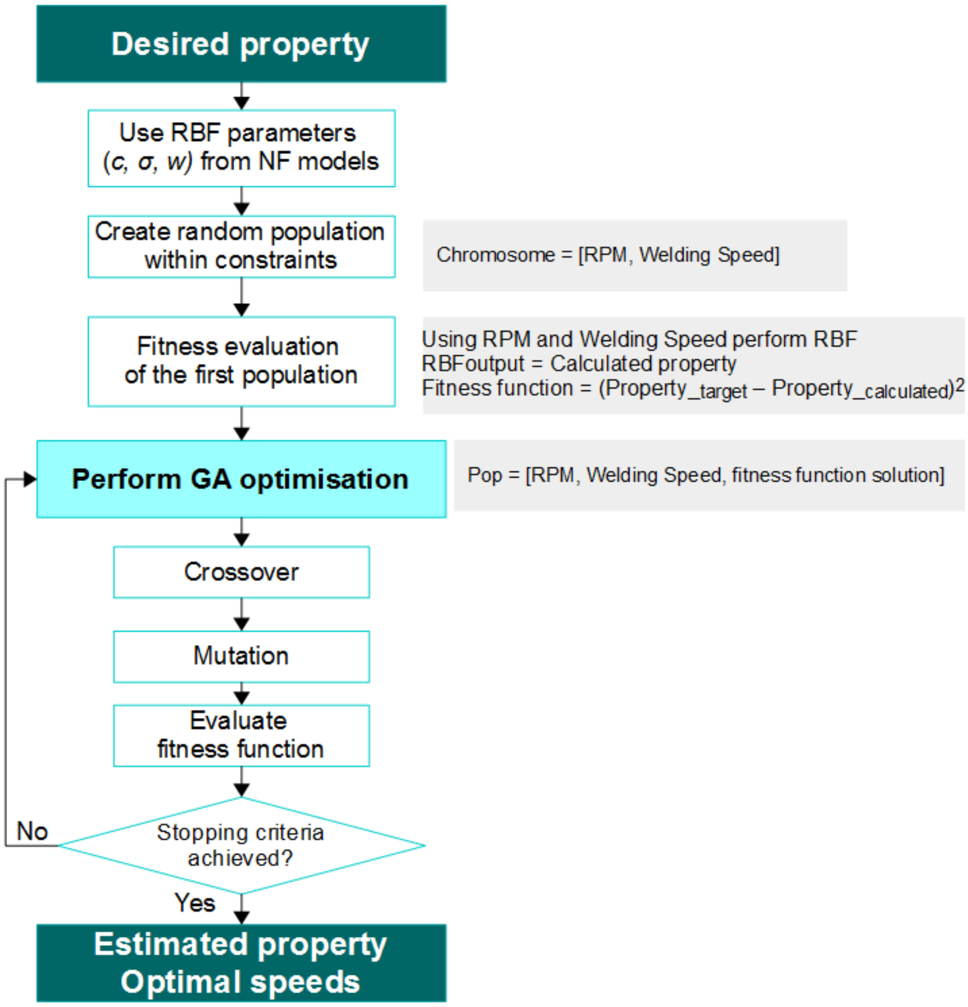

Figure 6.2 Flowchart of the GA optimisation for a single-objective problem

Using the information obtained from the previous NF models (c, σ, and ω), the structure of the chromosome can be defined. First, the variables to optimise are defined (N_{vars}). In this case $N_{vars} = 2$: Tool rotational speed ($Speed1$)and traverse speed ($Speed2$). Within the limits: $minSpeed1 \leq Speed1 \leq maxSpeed1$ and $minSpeed2 \leq Speed2 \leq maxSpeed2$.

$p_1 = Speed1, p_2 = Speed\ 2$

The initial population ($InitPop$) is built as follows:

$chromosome = [p_1, \ldots, p_{Nvars}]$

$InitPop = N_{pop} \times N_{vars}$

Where, N_{pop} is the population size.

The GA minimises the error between the desired property and the calculate property which is given by the RBF. Using Equation 6.3, the RBF computes the output of the system. During the evaluation of the fitness function, the GA generates possible solutions for the speeds $\left(Speed1_{optimalSol}\right)$, $\left(Speed2_{optimalSol}\right)$, and calculates the property value desired $\left(Property_{target}\right)$. When the termination criterion is achieved, the optimisation routine stops and the final optimal design can be obtained.

The demonstration of this algorithm is shown in the following Section. It will illustrate that the use of small populations can be used for the design of manufacturing processes without sacrificing the efficiency of the algorithm and enhancing the computational time.

6.3.1 Initial results on optimisation

The GA for a single-objective problem was performed to study the multiscale behaviour of FSW, i.e., optimal properties belonging to the POW of the NF models previously created have been evaluated. Figure 6.3 and Figure 6.4 clearly illustrate that, as previously discussed in the literature review, it is possible to achieve optimal results with the use of small populations and more importantly, the time to achieve the best solutions can significantly be reduced.

In Figure 6.3 the elongation desired was achieved in the 25th evaluation and the time for the evaluation was 1.68 seconds. On the other hand, Figure 6.4 shows that the elongation desired was achieve in the 5th evaluation in just 0.23 seconds. The simulations were performed for meso-scale and micro-scale properties of the FSW;

Table 6.1 summarises the encouraging results.

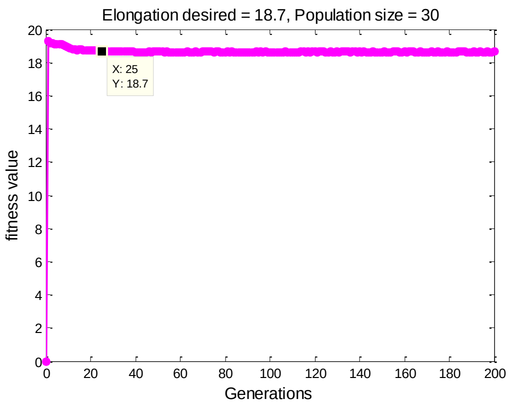

Figure 6.3 Average fitness of 10 runs vs. Generations to find the optimal design of elongation of FSW with elongation target = 18.7 (%) and population size = 30. Elapsed time (200 generations) = 1.68sec.

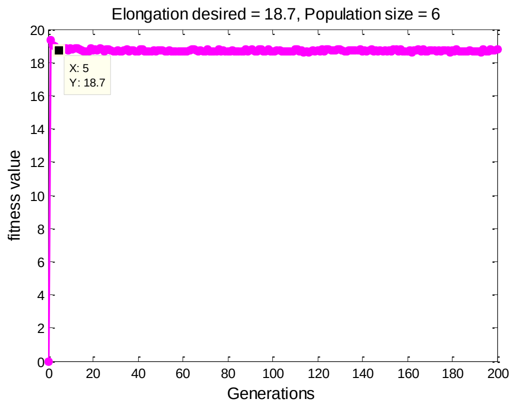

Figure 6.4 Average fitness of 10 runs vs. Generations to find the optimal design of elongation of FSW with elongation target = 18.7 % and population size = 6. Elapsed time (200 generations) = 0.23sec.

From the simulations performed in this Section, it can be conclude that the use of micro-GA is recommended to find the optimal design of FSW. In this case, the simulations evaluated showed that for populations = 6, the optimal design can be found within the 5th and 6th evaluations (see Table 6.1). Another important contribution regarding the use of small populations is that the computational efficiency of the algorithm, in terms of time, can be enhanced which leads to the use of this hybrid algorithms for real-time applications.

Table 6.1 Performance of population size for the optimal design of FSW for single-optimisation problems

FSW outputs predicted	*Desired property value*	*Fitness reached at evaluation (for population size =30)*	*Fitness reached at evaluation (for population size = 6)*
Elongation	18.7	25	5
ROA	20.3	28	6
UTS	310.6	26	5
YS	171.4	26	5
Average grain size	11.2	29	6
Cooling rate	66.5	26	6

The GA optimisation presented in this Section was applied for a single-objective problem, despite the results in terms of time and optimal design were encouraging, there is a need to develop systems that can optimise multiple objectives. For example in FSW the mechanical properties and microstructure can affect the overall quality of the joint, while users expect to achieve good mechanical properties, it is also important to ensure that the process parameters (speeds) will produce good quality welds. In the following section, the algorithm is updated for multi-objective optimisation and is applied to the optimal design of FSW.

Based on the encouraging results presented in Table 6.1, in terms of time and accuracy, further research was conducted to find the optimal solutions for multiple objectives. The results presented in this Section were obtained with small populations and the converge behaviour showed that the optimal solution can be reach within the 40th generation, reason why this criteria was used to develop a multi-objective optimisation framework for real-time applications.

6.4 A hybrid multi-objective optimisation framework based on micro-GA for the optimal design of manufacturing processes

In this Section, a fast multi-objective framework based on micro-GA is proposed for the optimal design of manufacturing processes; the general framework is presented in Figure 6.5. The framework consists of knowledge extracted from NF models presented in Chapter 4. The NF models were created with two inputs and one output. The several NF models used two FSW process parameters: tool rotational speed and traverse speed, to calculate different properties at different scales of the process, including, mechanical properties (elongation, reduction of area, ultimate tensile strength, and yield strength), microstructure (average grain size, cooling rate) and weld quality.

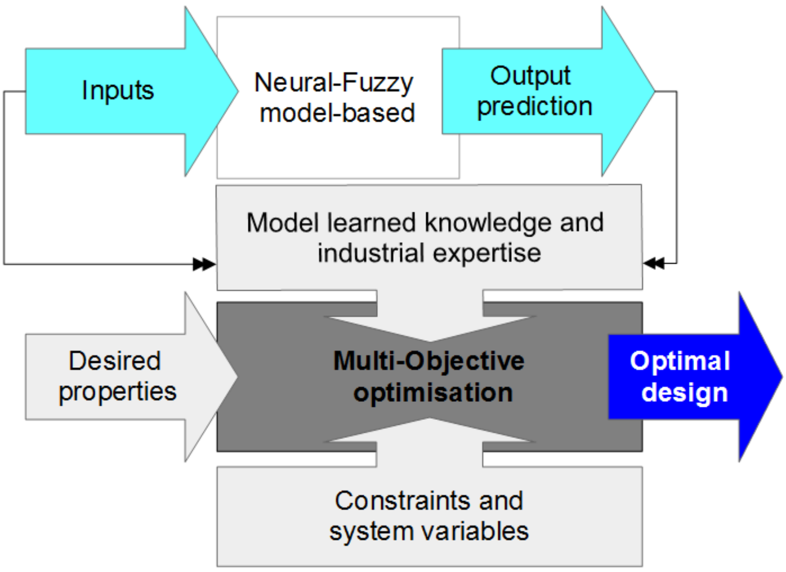

Figure 6.5 A multi-objective optimisation framework for the optimal design of manufacturing processes

As presented in the previous section, the knowledge learned in Chapter 4 from the RBF is used in this Chapter to create the initial population for the optimisation. In this Section, the multi-objective optimisation is based on a micro-GA, which optimises two objectives which are in conflict with each other (mechanical properties - weld quality, and microstructure - weld quality). More importantly, the proposed framework performs in real-time and estimates the optimal design of the system according to the settings given by the user (desired properties and constraints). This is the first time that a framework based on hybrid CI-modelling approaches is used with a micro-GA and applied for real-time and optimal design of FSW.

6.5 A real-time multi-objective algorithm to optimise and design the FSW process

The proposed algorithm which minimises two objectives, and estimates the optimal design of the FSW process is presented in Figure 6.6. For a multi-objective problem given as follows:

$$\begin{cases} \boldsymbol{Minimise\ f_1(x) = \left(p_{1(target)} - p_{1(calculated)}\right)^2} \\ \boldsymbol{Minimise\ f_2(x) = \left(p_{2(target)} - p_{2(calculated)}\right)^2} \\ \qquad\qquad\qquad \boldsymbol{Subject\ to} \\ \boldsymbol{(i)} \qquad \boldsymbol{-2\%\ p_{1(target)} \leq p_1 \leq +2\%\ p_{1(target)}} \\ \boldsymbol{(ii)} \qquad \boldsymbol{min_{p_2} \leq p_2 \leq max_{p_2}} \\ \boldsymbol{(iii)} \qquad \boldsymbol{min_{Speed} \leq Speeds \leq max_{Speed}} \end{cases} \qquad \boldsymbol{(6.4)}$$

Where p_1 is the target of the parameter from the manufacturing process that is needed to be optimised together with the weld quality (p_2). The parameters to optimise in this Chapter are the mechanical properties (elongation, ROA, UTS and YS) and microstructure properties (average grain size and cooling rate) of the welds produced by FSW. The constrains are proposed based on expert knowledge with the aim of optimise the parameters within the POW, for instance, the boundaries of constrain (i) -/+ 2% are set to achieved good mechanical properties, constrains (ii) and (iii) are the speed limits (traverse speed and rotational speed) which reflect the maximum and minimum values of speeds to maintain the system within its optimal POW.

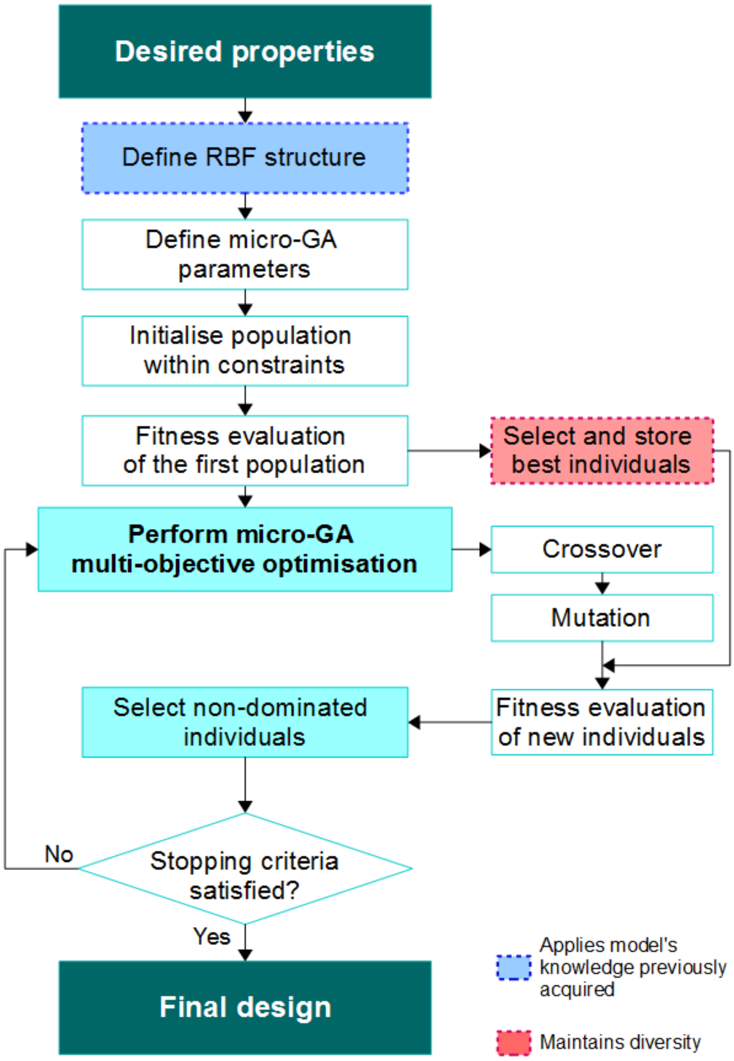

Figure 6.6 Flowchart of the multi-objective optimisation for FSW

The proposed multi-objective optimisation includes the following steps:

Step 1:	Set up desired properties: user defines desired properties from the system $(p_{1(target)}, p_{2(target)})$.
Step 2:	Assign optimised RBF parameters: from previous training knowledge (Chapter 4), extract centres $(c_1 \dots c_r)$, sigma $(\sigma_1 \dots \sigma_r)$, and weights $(\omega_1 \dots \omega_r)$ values, where $r = number\ of\ rules$.

Step 3: Define micro-GA parameters: for this Chapter, generations = 200 (Gen); population size = 6 (N_{pop}); mutation rate = 0.02 (mut_{rate}); crossover rate = 0.3 $(cross_{rate})$; number of variables to optimise = 2 (N_{vars}).

Step 4: Randomly generate the initial population within constrains (Haupt and Haupt, 2004) p. 54. Using constraints given in Equation 6.4 (iii).

$$InitPop = N_{pop} \times N_{vars}$$

$$Init_{popM} = \begin{bmatrix} x_{1,1} & x_{i,1} \\ x_{1,j} & x_{i,j} \end{bmatrix} \; i = N_{vars}; j = N_{pop}$$

Step 5: The initial population $(Init_{popM})$ and previous knowledge variables $(c, \sigma, \omega, N_{inputs}, N_{rules})$ are used to estimate $p_{1(calculated)}$ and $p_{2(calculated)}$ using the following equation:

$$p_{calculated} = RBF_{out}(N_{rules}, N_{inputs}, c, \sigma, \omega, [Init_{popM_{i,j}}])$$

RBF_{out} is calculated using Equation 6.3.

Step 6: Evaluate the fitness function of the first population by minimising both:

$$f_1(x) = \left(p_{1(target)} - p_{1(calculated)}\right)^2$$

$$f_2(x) = \left(p_{2(target)} - p_{2(calculated)}\right)^2$$

Step 7: Randomly select a set of individuals that will be used to maintain diversity of the micro-GA:

(i) Generate a random number (ran_{number}) which is $< j$

(ii) Set 1 of best individuals is generated from the set of solutions $f_1(x)$ which are closest to $p_{1(target)}$. The number of individuals which are selected for set 1 is decided by $ran_{number}/2$

(iii) Set 2 of best individuals is generated from the set of solutions $f_2(x)$ which are closest to $p_{2(target)}$. The number of individuals which are selected for set 2 is decided by $ran_{number}/2$

(iv) A combination of both sets creates a set of best individuals $(BestInd_{diversity})$ which is then used to maintain diversity.

Step 8: After evaluation of the fitness function of the first generation, a pool of solutions is generated:

$$PoolSol = [x_1, x_2, f_1, f_2]$$

Step 9: Using $olSol$, perform micro-GA multi-objective optimisation as follows:

Step 10: Execute stochastic uniform selection and single point crossover for $PoolSol$ (Haupt and Haupt, 2004) , then randomly mutate individuals (Deb, 2001) p.122.

Step 11: Combining the mutated individuals and $BestInd_{diversity}$ a more diverse set of new individuals is created.

Step 12: Evaluate the fitness function of the new individuals. Optimise the problem according to objectives and constraints given in Equation 6.4.

Step 13: Select non dominated individuals to start next generation and find the Pareto optimum solutions according to

Equation 6.1 (Deb et al., 2002).

Step 14: Repeat steps 9-13 until stopping criterion is achieved (for this algorithm, stopping criterion: maximum number of generations, time limit of two seconds).

6.5.1 Experimental results and simulations

In this Section, details relating to finding the optimal solutions (tool rotational and traverse speeds) for achieving predefined mechanical properties and microstructure values of the FSW are presented. Six models are created to: (i) describe the behaviour of the FSW at its different scales (micro, meso and micro-scale) (ii) achieved predefined properties within boundaries, (iii) find the possible candidate solutions for the multi-objective problem. The efficiency of this algorithm is given by the little information that the system needs to produce a set of various solutions and also the low computational cost is demonstrated. The latter was achieve by different contributions: (i) the constrains are used to reduce and guide the search space which reduces the evaluation time (ii) the multi-objective optimisation based on micro-GA uses a small population and maintains a good diversity (iii) for the future implementation of this algorithm in real-time applications, the stopping criteria is based on time (no more than 2 seconds evaluation time).

Model 1: elongation and weld quality

The first model produces a set of optimal solutions for the elongation target = 18.7% and weld quality ≤ 1.3. The constraints used for this simulation were strictly limited to only +/-2% of the elongation target value (+2% = 19.07; -2% 18.32). The design problem for model 1 can be described as follows:

$$\boldsymbol{Objective_1} = \left(Elongation_{\,(target)} - Elongation_{(calculated)}\right)^2$$
$$\boldsymbol{Objective_2} = \left(Weld\ Quality_{(target)} - Weld\ Quality_{(calculated)}\right)^2$$

$$\boldsymbol{Subject\ to}$$
$$(i) - 2\%\ Elongation_{\,(target)} \leq Elongation \leq +2\%\ Elongation_{\,(target)}$$
$$(ii)\ 0 \leq Weld\ Quality \leq 1.3$$
$$(iii)\ minTS \leq Traverse\ speed \leq maxTS$$
$$(iv)\ minRPM \leq RPM \leq maxRPM$$

It can be observed in Figure 6.7, that the solutions are located between the design constraints. The six different solutions around the elongation and weld quality target values are listed in Table 6.2. The time for this evaluation was 0.30 seconds.

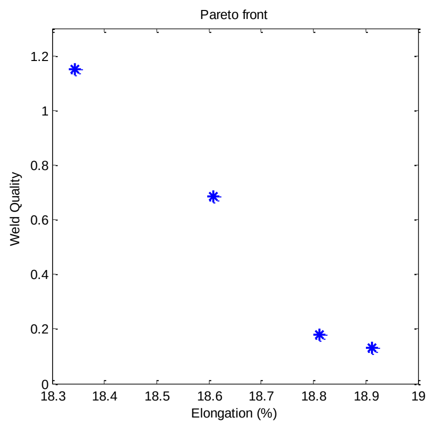

Figure 6.7 Pareto optimal solutions: elongation (%) and weld quality

Table 6.2 Pareto optimal solutions model 1: elongation and WQ

Solutions	RPM	Traverse Speed	Elongation (%) Calculated	WQ Calculated
1	280.0	168.0	18.3	1.2
2	406.1	262.6	18.6	0.7
3	406.1	474.9	18.6	0.7
4	537.9	262.6	18.8	0.2
5	537.9	474.9	18.8	0.2
6	580.0	515.5	18.9	0.1

Figure 6.8, Figure 6.9, and Figure 6.10 show the behaviour of the POW for the Pareto front for both solutions. Figure 6.11 shows the behaviour of the Pareto optimal solutions for real-time applications, this plot will describe to the final user the performance of both elongation and WQ. This approach can be used as a support for decision making and monitoring the quality of the welds during the FSW process.

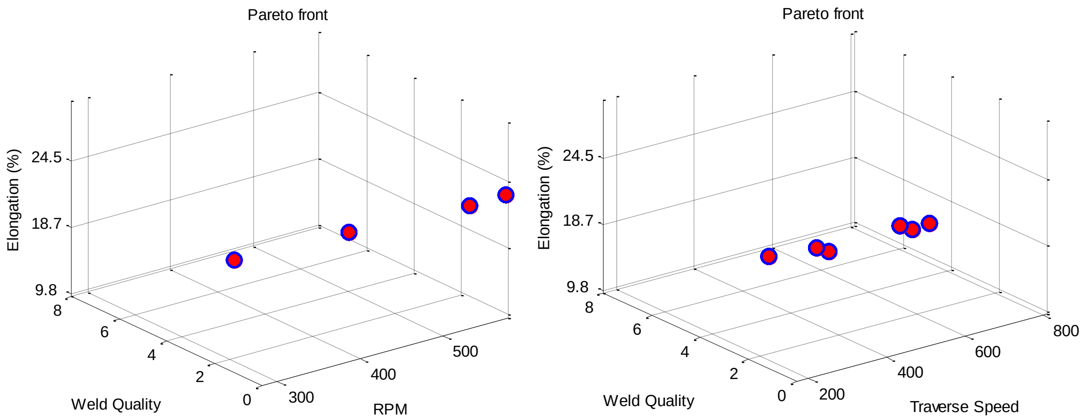

Figure 6.8 POW of Pareto optimal solutions and speeds

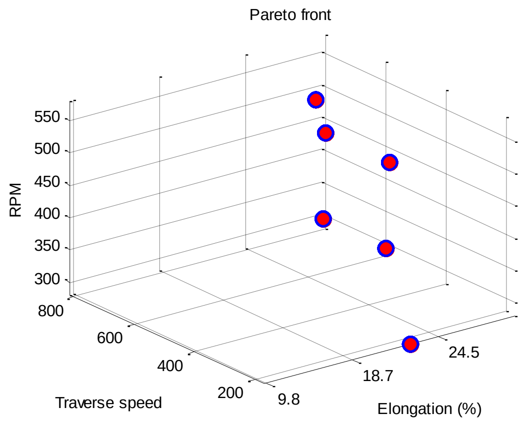

Figure 6.9 POW of Pareto optimal solutions of elongation and speeds

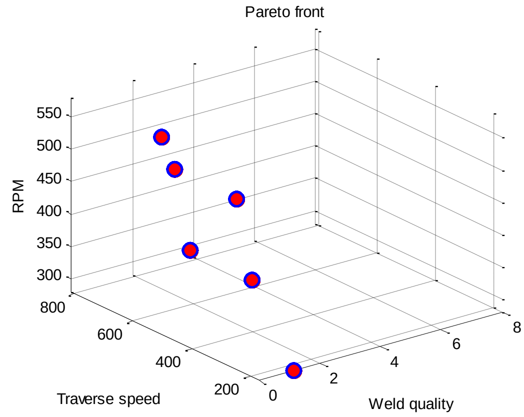

Figure 6.10 POW of Pareto optimal solutions of weld quality and speeds

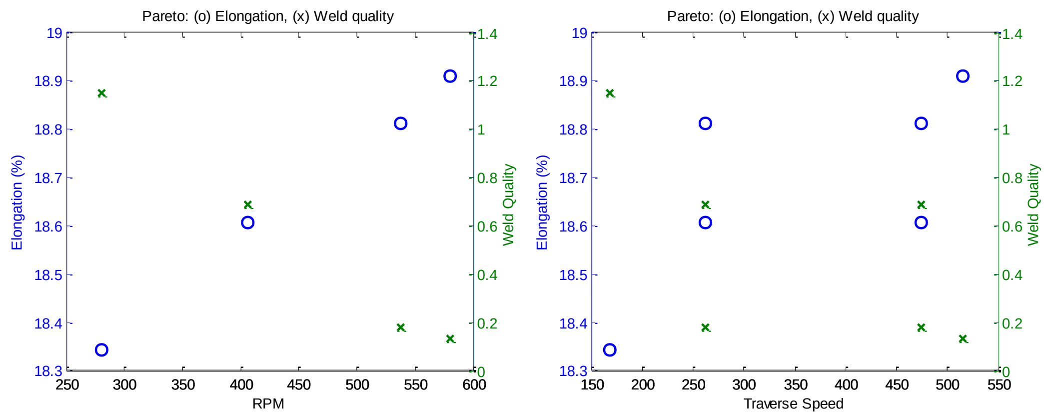

Figure 6.11 Pareto optimal solutions of elongation (%) - weld quality and speeds, plot presented to the final user for real-time applications

Model 2: reduction of area

Model 2, produces a set of optimal solutions for the ROA = 20.3% and weld quality ≤ 1.3. The constraints used for this simulation were also +/-2% of the ROA target value (+2% = 20.71; -2% 19.90). The design problem for model 2 can be described as follows:

$$\boldsymbol{Objective_1} = \left(ROA_{\,(target)} - ROA_{(calculated)}\right)^2$$
$$\boldsymbol{Objective_2} = \left(Weld\ Quality_{(target)} - Weld\ Quality_{(calculated)}\right)^2$$

$$\boldsymbol{Subject\ to}$$
$$(i) - 2\%\ ROA_{\,(target)} \leq ROA \leq +2\%\ ROA_{\,(target)}$$
$$(ii)\ 0 \leq Weld\ Quality \leq 1.3$$
$$(iii)\ minTS \leq Traverse\ speed \leq maxTS$$
$$(iv)\ minRPM \leq RPM \leq maxRPM$$

The five different solutions around the ROA and weld quality target values are listed in Table 6.3 . The time for this evaluation was 0.34 seconds.

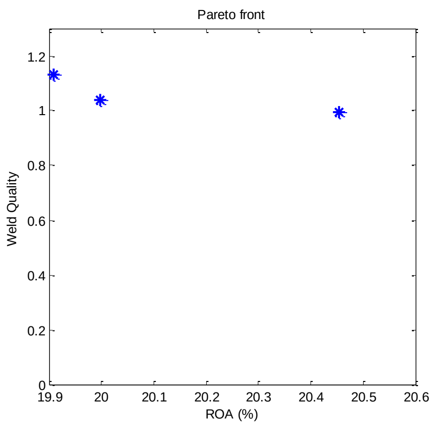

Figure 6.12 Pareto optimal solutions: reduction of area (%) and weld quality

Table 6.3 Pareto optimal solutions model 2: reduction of area

Solutions	RPM	Traverse speed	ROA (%) calculated	WQ calculated
1	280.0	174.0	19.9	1.1
2	351.5	168.0	20.0	1.0
3	396.2	318.0	20.5	1.0
4	396.2	732.5	20.5	1.0
5	396.2	812.0	20.5	1.0

Model 3: UTS

Model 3, produces a set of optimal solutions for the UTS = 310.6 (MPa) and weld quality ≤ 1.3. The constraints used for this simulation were also +/-2% of the UTS target value (+2% = 316.81; -2% 304.34). The design problem for model 3 can be described as follows:

$$\boldsymbol{Objective_1} = \left(UTS_{\,(target)} - UTS_{(calculated)}\right)^2$$
$$\boldsymbol{Objective_2} = \left(Weld\ Quality_{(target)} - Weld\ Quality_{(calculated)}\right)^2$$

$$\boldsymbol{Subject\ to}$$
$$(i) - 2\%\ UTS_{\,(target)} \leq UTS \leq +2\%\ UTS_{\,(target)}$$
$$(ii)\ 0 \leq Weld\ Quality \leq 1.3$$
$$(iii)\ minTS \leq Traverse\ speed \leq maxTS$$
$$(iv)\ minRPM \leq RPM \leq maxRPM$$

The five different solutions around the UTS and weld quality target values are showed in Figure 6.13 and listed in Table 6.4. The time for this evaluation was 0.33 seconds.

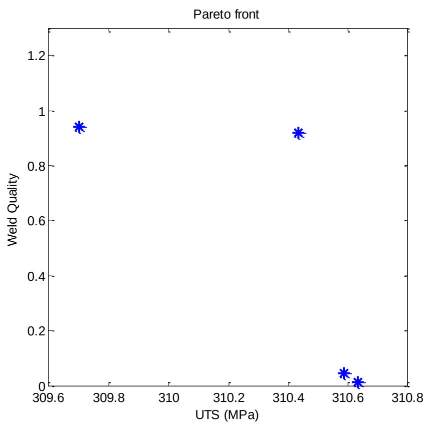

Figure 6.13 Pareto optimal solutions: ultimate tensile strength (MPa) and weld quality

Table 6.4 Pareto optimal solutions model 3: ultimate tensile strength

Solutions	RPM	Traverse speed	UTS (MPa) calculated	WQ calculated
1	280.0	339.6	310.6	0.0
2	280.0	812.0	310.6	0.0
3	424.2	522.3	310.6	0.0
4	430.2	168.0	310.4	0.9
5	580.0	195.3	309.7	0.9

Model 4: yield strength

In this model, a set of optimal solutions for YS = 171.4 (MPa) and weld quality ≤ 1.3 are produced. The constraints used for this simulation were also +/-2% of the YS target value (+2% = 174.83; -2% 167.97). The design problem for model 4 can be described as follows:

$$\boldsymbol{Objective_1} = \left(YS_{\,(target)} - YS_{(calculated)}\right)^2$$
$$\boldsymbol{Objective_2} = \left(Weld\ Quality_{(target)} - Weld\ Quality_{(calculated)}\right)^2$$

$$\boldsymbol{Subject\ to}$$
$$(i) - 2\%\ YS_{\,(target)} \leq YS \leq +2\%\ YS_{\,(target)}$$
$$(ii)\ 0 \leq Weld\ Quality \leq 1.3$$
$$(iii)\ minTS \leq Traverse\ speed \leq maxTS$$
$$(iv)\ minRPM \leq RPM \leq maxRPM$$

The five different solutions around the YS and weld quality target values are showed in Figure 6.14 and listed in Table 6.5. The time for this evaluation was 0.32 seconds.

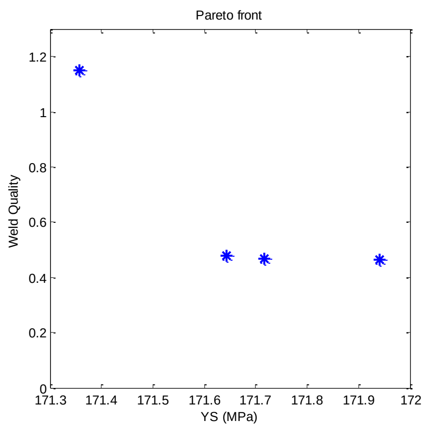

Figure 6.14 Pareto optimal solutions: yield strength (MPa) and weld quality

Table 6.5 Pareto optimal solutions model 4: yield strength

Solutions	RPM	Traverse speed	YS (MPa) calculated	WQ calculated
1	280.0	168.0	171.4	1.2
2	337.1	812.0	171.9	0.5
3	453.7	313.8	171.7	0.5
4	580.0	378.3	171.6	0.5
5	280.0	168.0	171.4	1.2

Model 5: average grain size

In this model, a set of optimal solutions for the average grain size = 11.2 (μm) and weld quality ≤ 1.3 are produced. The constraints used for this simulation were also +/-2% of the average grain size target value (+2% = 11.42; -2% 10.98). The design problem for model 5 can be described as follows:

$$\boldsymbol{Objective_1} = \left(AGrainSize_{\,(target)} - AGrainSize_{\,(calculated)}\right)^2$$
$$\boldsymbol{Objective_2} = \left(Weld\ Quality_{(target)} - Weld\ Quality_{(calculated)}\right)^2$$

$$\boldsymbol{Subject\ to}$$
$$(i) - 2\%\ AGrainSize_{\ (target)} \leq AGrainSize \ \leq +2\%\ AGrainSize_{\ (target)}$$
$$(ii)\ 0 \leq Weld\ Quality \leq 1.3$$
$$(iii)\ minTS \leq Traverse\ speed \leq maxTS$$
$$(iv)\ minRPM \leq RPM \leq maxRPM$$

The six different solutions around the average grain size and weld quality target values are showed in Figure 6.15 and listed in Table 6.6. The time for this evaluation was 0.32 seconds.

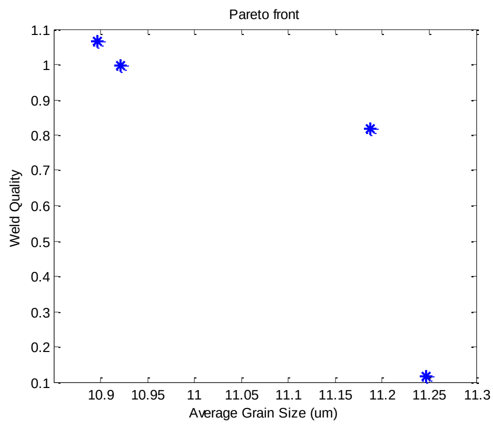

Figure 6.15 Pareto optimal solutions: average grain size (μm) and weld quality

Table 6.6 Pareto optimal solutions model 5: average grain size

Solutions	RPM	Traverse speed	Grain size (μm) calculated	WQ calculated
1	280.0	306.4	10.9	1.0
2	334.7	168.0	10.9	1.1
3	567.5	237.7	11.2	0.8
4	567.5	306.4	11.2	0.8
5	580.0	522.0	11.2	0.1
6	580.0	812.0	11.2	0.1

Model 6: cooling rate

In this model, a set of optimal solutions for the average grain size = 66.5 (˚C/s) and weld quality ≤ 1.3 are produced. The constraints used for this simulation were also +/-2% of the cooling rate target value (+2% = 67.83; -2% 65.17). The design problem for this model can be described as follows:

$$\boldsymbol{Objective_1} = \left(Cooling\ Rate_{\ (target)} - \ Cooling\ Rate_{(calculated)}\right)^2$$
$$\boldsymbol{Objective_2} = \left(Weld\ Quality_{(target)} - \ Weld\ Quality_{(calculated)}\right)^2$$

$$\boldsymbol{Subject\ to}$$
$$(i) - 2\%\ Cooling\ Rate_{\ (target)} \leq Cooling\ Rate \leq +2\%\ Cooling\ Rate_{\ (target)}$$
$$(ii)\ 0 \leq Weld\ Quality \leq 1.3$$
$$(iii)\ minTS \leq Traverse\ speed \leq maxTS$$
$$(iv)\ minRPM \leq RPM \leq maxRPM$$

The six different solutions around the average grain size and weld quality target values are showed in Figure 6.16 and listed in Table 6.7. The time for this evaluation was 0.30 seconds.

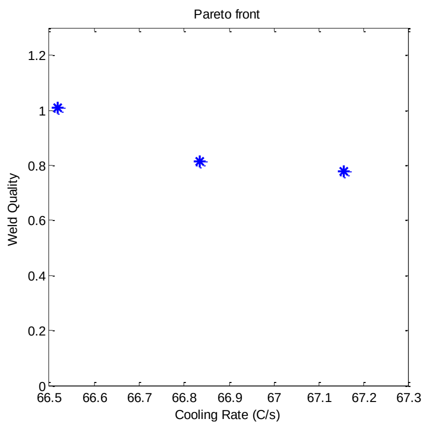

Figure 6.16 Pareto optimal solutions: cooling rate (˚C/s) and weld quality

Table 6.7 Pareto optimal solutions model 6: cooling rate

Solutions	RPM	Traverse speed	Cooling rate (˚C/s) calculated	WQ calculated
1	327.0	168.0	67.2	0.8
2	327.0	277.8	67.2	0.8
3	327.0	310.9	67.2	0.8
4	327.0	758.5	67.2	0.8
5	483.4	182.6	66.8	0.8
6	580.0	168.0	66.5	1.0

As presented in Sections 6.1 and 6.2, a micro-GA optimisation algorithm has been applied for multi-objective problems and some efforts have been made for manufacturing problems, however, most of the publications reviewed did not present results in terms of time evaluation of their algorithms, for this reason it is challenging to compare the presented results. Nevertheless, these results can be compared with the work presented by (Coello and Pulido, 2001b), the authors analyse four test functions commonly proposed in the literature review to compare three algorithms including, NSGA II, PAES and micro-GA. The results are reported over 20 runs and the micro-GA shows the best average running time which for the four test functions is 1.7 seconds. The results presented in this Chapter to optimise two objectives of the FSW and find its optimal design were evaluated over 10 runs and the average running time of the six models was 0.32 seconds, which is suitable for using in FSW for taking decisions in 'near real-time'. In terms of the quality of the proposed results, it is shown that there is close agreement between the target objectives and the achieved solutions while also the achieved solutions appear to be (based on expert process knowledge) feasible from a process perspective.

The proposed framework has the ability to find the optimal design (process parameters) for a complex manufacturing process. The converge speed, accuracy of the predictions and total time of the system development make this approach an attractive technique suitable for online monitoring the condition of the FSW process. The multi-objective optimisation proposed can be used as a tool to design the optimal POW for aluminium alloys, hence, it has the potential to reduce production costs and at the same time monitor the quality of the welds produced by FSW. The solutions are selected from a 'pool' of Pareto front solutions, which in our case could be done by an expert. To achieve a real autonomous real-time system operation, one would need to also develop a solution selection mechanism, to allow the system to select one solution only in real time; however this is not within the scope of this thesis. One could achieve this, by investigating multi-criteria decision-making methods (Coello, Aguirre, and Zitzler, 2001; Carlos M

Fonseca, Fleming, Zitzler, Deb, and Thiele, 2003; Purshouse, Fleming, Fonseca, Greco, and Shaw, 2013).

6.6 Summary

In this Chapter, a new multi-objective optimisation algorithm based on hybrid CI modelling techniques such as micro-GA and RBF was presented. The algorithm extracts knowledge from previous NF models and integrates the experience from process experts to achieve the optimal design of complex manufacturing processes and find the Pareto optimal solutions of two functions. The use of micro-GA which consists of very small populations (based on preliminary results, the population size in this Chapter was set to only six) and a routine which maintains diversity based on the best individuals, was proposed in this Chapter because it is computationally inexpensive and is highly suited for real-time applications.

The multi-objective optimisation presented in this Chapter, contributes to better understanding of complex manufacturing processes, in this case, for FSW. The simulations presented, allowed the study of this process at its various scales and the location of the optimal POW, factors that are key for industries when designing effective production schedules. The framework may be used as a tool for decision making and design of control quality approaches which can ensure the production of free-defect welds.

The various simulations presented in this Chapter have found the optimal solutions for the design of two objectives which are usually in conflict with each other. Six multi-objective problems were presented to the framework to find the Pareto optimal of solutions which are based on the set up of the parameters given by the speeds. Due to the small set of welding data available to find the optimal design of FSW, the Pareto of optimal solutions consisted on average of only six solutions. This means that the user will be presented with a small quantity of information which may be helpful when taking decisions and designing the optimal POW's.

The results presented in this Chapter were performed for aluminium alloys AA5083 and using MX Tri-Flute tool, it is recommendable to evaluate the response of the proposed framework for different materials and tool designs. It will also be worth studying different techniques to maintain a good diversity for micro-GA.

Concisely, the contributions of the investigation presented in this Chapter can be listed as follows: (i) For the first time, a new multi-objective optimisation framework based on micro-GA, hybrid CI approaches, and expert knowledge was presented; (ii) Micro-GA was proposed as an optimisation tool which has considerably reduced the computational cost of this algorithm; (iii) the algorithm is suited for real-time applications and the design of POW's of complex manufacturing processes; (iv) the framework has the ability to find optimal parameters (tool rotational and traverse speed) within a strictly constrained search space; (v) for the first time, the trade-off between the various mechanical properties (elongation, ROA, UTS, and YS) and weld quality was studied, similarly, the micro-scale of the FSW was investigated for the trade-off between microstructure (average grain size, cooling rate) and weld quality.

The framework presented in this Chapter may be used as integration of a more complete system for predicting, monitoring, evaluating, and optimising the multi-objective problems presented in manufacturing processes.

7 Conclusions and Future Work

Overview

In this thesis, the use of data-driven models has been proposed as an alternative solution to numerical modelling, for the understanding and optimisation of complex manufacturing processes. Key research challenges include the availability of only a conservative number of data samples, as well as the creation of HCS and real-time computational frameworks. The data-driven models are based on hybrid CI structures, which use the best characteristics of FL Systems, NN, evolutionary algorithms and multi-objective optimisation to describe, predict, monitor and optimise the performance of complex manufacturing processes. FSW has been utilised as the case study for this research work, representing a complex and so far ill-understood thermomechanical process. It is worth highlighting that the computational framework presented in this thesis is specific to FSW; it can be extended, however, to applications in other manufacturing sectors. A summary follows, of the main research results and the new contributions that this PhD project has made to better understanding of this welding technique, as well as in the discipline of Systems Engineering and CI.

7.1 Summary of main results and contributions

In this thesis, the background and motivation of this investigation were presented, the main issues related to the modelling of complex manufacturing systems were discussed and the challenges related to the modelling of FSW were presented.

To begin with, the FSW process was reviewed from a theoretical and practical perspective in order to demonstrate the significance of this novel technique for industry, and also to expose the complex phenomena and engineering challenges involved in this manufacturing process. The current literature on processing variables, tool design, and materials was presented with the aim of gaining a deeper understanding of the process. The advantages and disadvantages of this welding technique were also addressed. The literature presented revealed that one of the main advantages of this welding technique is the quality of welds. For this reason, there is a specific interest from companies to develop techniques that can provide significant information about the quality and characteristics of the products, without the need of destructive testing techniques. It was also identified the lack of intelligent systems that can monitor the process in real-time and, at the same time, can detect the behaviour which influence the quality of the final welds. Evidence presented revealed that one of the main challenges to simulate FSW is the development of models that can describe the complex interactions involved in this process. These include heat generation, material flow, and the influence of welding parameters over the final weld.

Based on the findings from the literature review, preliminary data-driven modelling techniques based on CI were proposed to create computational models of complex industrial processes. Particular challenges related to the development of intelligent models for FSW were discussed. More importantly, it was identified the lack of intelligent techniques which are able to effectively monitor the process for real-time applications and at the same time can communicate significant information on the performance of the process.

Chapter 7. *Conclusions and Future Work*

Multiscale and data-driven modelling techniques were proposed as computational tools which can analyse and simulate complex industrial processes. The models were developed using NF modelling approaches. The ability of these CI paradigms based on Fuzzy Systems and NN to learn from data, and predict behaviour of complex systems, was demonstrated. It was also demonstrated that by using these techniques, a better understanding of complex interactions present in manufacturing processes can be achieved at multiple scales. More importantly, the multiscale models assist the process experts to better comprehend and identify the POW's of the process under investigation.

The NF models presented in this investigation have successfully simulated a complex manufacturing process, in this case FSW. The transparency of the NF models was demonstrated, and the inherent interpretability, due to the use of FL, of these models was exemplified with the use of IF-THEN sentences. It was demonstrated that NF-models can be translated into natural human reasoning which help experts better understand the complex interactions of their systems. The main contribution described in this Chapter was to prove that NF modelling can accurately predict the behaviour of FSW, even with few parameters and small data samples, by providing appropriate model training and optimisation techniques. The multiscale NF models were produced with only two inputs: tool rotational speed and traverse speed. Various process characteristics were also evaluated, including mechanical performance, microstructural characterisation and high-level product quality assessment. The NF models predicted crucial mechanical properties of the materials welded by FSW. Elongation, ROA, UTS and YS were accurately predicted for aluminium alloys AA5083. The microstructure of the material was evaluated by simulating the process data at two different scales: average grain size and cooling rate. Furthermore, the performance of the models was successfully simulated to predict the quality of welds produced by FSW.

In this investigation, for the first time, a multiscale approach was developed to gain insights into FSW. This is a significant contribution for process experts as the models have been used as tools to study in depth the complex interactions within the system, as well as its influence over the whole FSW process at three different scales (micro-, meso- and macro-). This was achieved while using only a conservative number of data samples (experiments) which were carefully designed in collaboration with the process experts at TWI Ltd.

Another important contribution from the multiscale models presented in this thesis, was the creation of a NF model, which can simulate the cooling rate using thermal information from the process. The experimental approach was based on thermal imaging recordings, and extraction of relevant features, which was carried out at Cambridge, at TWI Ltd. facilities. This is a promising approach, which can potentially be used for real-time applications.

Two significant contributions were presented in this thesis, both relevant to systems engineering and CI: (i) An NF model approach-based on spectral-temporal analysis and (ii) a GA-RBF optimisation, which further improves the performance of the multiscale models. A NF model-based approach was successfully developed, allowing the in-depth analysis of the multiscale behaviour of the FSW process. The use of spectral-temporal analysis was proposed as the main vehicle to capture process information from bending forces. This approach was enabled by creating a feature extraction process, out of the spectral-temporal data, which relates to the identification of suitable markers in the spectral domain. It was demonstrated how the tool bending force measurements can be used, via the FFT-based markers, to directly predict the final weld quality of the materials welded using FSW. The hypothesis, which was confirmed, was that the vibration and force profile of the tool's bending forces are directly linked to the final product quality. The contribution of the spectral-temporal analysis can be extended to the potential reduction of the number of monitoring channels, which are currently used to collect the bending forces information. This can lead in the future to the development of simpler instrumentation of monitoring tools. The spectral-temporal models may be used as a form of non-destructively evaluating the process' performance. More importantly, the models based on spectral analysis of the bending forces may be used for real-time applications; this is due to the low computational cost of the RBF-based modelling structure.

The aim of presenting a GA-RBF optimisation was to demonstrate that even with a few data samples, the models previously developed can be further improved by using hybrid techniques. The hybrid modelling techniques proposed used: (i) FCM, to classify the data, and create the rules which describe the system; (ii) GA, to search for optimum solutions, and (iii) RBF, to improve the learning process of the model. A clear enhancement of the multiscale models of the FSW process was presented.

A further significant contribution was the development of a new computational framework for model-based monitoring of manufacturing processes was created. The new framework is based on Fuzzy Entropy, and makes use of a model-based approach to autonomously identify abnormal process behaviour. The fuzzy entropy proposed is based on a Shannon's entropy criterion. An NF modelling structure was used to develop the core knowledge of the system, while a FCM algorithm along with a GA were used for the system's parametric optimisation.

Several contributions were presented in this investigation: namely, the use of Fuzzy Entropy to measure information in model-created data, as well as taking advantage of the linguistic interpretability of the FL systems to create a HCS capable of providing feedback to the user automatically via natural language. The proposed HCS framework presents information relevant to the system's performance and detects new behaviour.

The proposed approach was successfully applied to FSW in order to study its complex and non-linear process conditions and predict the weld quality of the materials welded using this technique. This framework was applied for the first time to investigate experimental, real and synthetic datasets which evaluate the quality of the material. The results of these experiments, demonstrated the linguistic feedback of the system for the three industrial-based scenarios. Furthermore, the system's computational efficiency allows it to run in real-time. This was demonstrated in the synthetic data experiments, which emulate real-life operating conditions. The framework has the potential to be used as an autonomous/semi-autonomous system for monitoring complex manufacturing processes in real-time while, also providing linguistic feedback to experts and non-experts.

A multi-objective optimisation algorithm based on hybrid CI modelling techniques micro-GA and RBF was presented. The algorithm extracts knowledge from previous NF models to achieve the optimal design of complex manufacturing processes. The proposed framework is computational inexpensive and highly suited for real-time applications. The framework may be used as a tool for decision making and design of control quality approaches which can ensure the production of free-defect welds.

The various simulations presented in this investigation have found the optimal solutions for the design of two objectives which are usually in conflict which each other. Six multi-objective problems were presented to the framework to find the Pareto optimal front of solutions which are based on the set up of the parameters given by the speeds. Due to the small set of welding data available to find the optimal design of FSW, the Pareto front of optimal solutions consisted in average of only six solutions. This means that the user was presented with a conservative quantity of information which may be helpful when taking decisions and designing the optimal POW's.

Concisely, the contributions of this investigation can be listed as follows: (i) a new multi-objective optimisation framework based on micro-GA, hybrid CI approaches, and expert knowledge was presented; (ii) a micro-GA was proposed as a optimisation tool for multi-objective problems which has considerably reduced the computational cost of this algorithm; (iii) the algorithm is suited for real-time applications and the design of POW's of complex manufacturing processes; (iv) the framework has the ability to find optimal parameters (tool rotational and traverse speed) within a strictly constrained search space; (v) for the first time, the trade-off between the various mechanical properties (elongation, ROA, UTS, and YS) and weld quality was studied, similarly, the micro-scale of the FSW was investigated for the trade-off between microstructure (average grain size and cooling rate) and weld quality. The framework may be used as an integrated system for predicting, monitoring, evaluating, and optimising the multi-objective problems presented in manufacturing processes.

The data-driven models and frameworks presented in this thesis, have contributed to better understanding of FSW, while also created new systems engineering tools and methodologies based on CI to address specific challenges related to FSW. Data-driven modelling techniques have proved their ability of learning from data and describe complex industrial processes even when small datasets are available. Several novel techniques were proposed to analyse FSW and predict the quality of the welds. The proposed techniques were NF modelling, spectral analysis and novelty detection. These techniques extract significant information from complex systems and simplify the models presented to the user. The develop techniques have the ability to communicate in a natural language with the user. The use of multi-objective optimisation was proposed to achieve optimal design of FSW. The approaches are computationally inexpensive and potential applications for real-time systems can be developed. With further research and development, the studies presented in this thesis can be extended into other manufacturing processes.

Although only limited information is available in the public domain (Research Excellence Framework, 2014), it is worth mentioning that the use of the data-driven models for FSW presented in this thesis has already had a significant impact for industries, particularly for the aerospace sector. The data-driven models and optimisation frameworks have been used by TWI for a number of their industrial partners which has resulted in the reduction of extensive and expensive experimentation. The reductions of experiments lead to notable savings on: product development times of 50%, reduction of costs of 25% and significant reduction of materials needed for expensive weld trials. Furthermore, online monitoring frameworks based on real-time optimisation have contributed to the development of a relevant ISO certification for FSW applications. In terms of environmental impact, the production of lightweight aerospace components and structures which have been possible through the use of the developed data-driven and optimisation models, this has led to the improvement of fuel efficiency which also results in less CO_2 emissions.

The results presented in this thesis were performed for aluminium alloys only, it is recommended to evaluate the response of the proposed algorithms for different materials and tool designs, perhaps materials with more complex microstructure behaviour (e.g. steel). In terms of the GA optimisation, it will be worth studying different techniques to maintain and improve the diversity. The simulations presented in Chapter 6 were produced for two objectives, it would be helpful to increase the number of objectives and evaluate the time that the algorithm takes to find the optimal solutions with more than two objectives. The solutions presented were selected from a 'pool' of Pareto front solutions, to achieve an autonomous real-time system operation, one would need to develop a solution selection mechanism, to allow the system to select one solution only in real time, however this is not within the scope of this thesis. The proposed selection could be achieved by investigating multi-criteria decision-making methods (Coello et al., 2001; Carlos M Fonseca et al., 2003; Purshouse et al., 2013). A limitation of the developed models was the over-fitting, where the model tried to learn from data that has never been presented to the system; the learning routine of the models can be improved with weld data generated within the 'poor' welding zone.

7.2 Future research directions

Based on the studies described in this investigation, some future research directions can be suggested:

The NF models presented in this thesis have used dataset from aluminium alloys AA5083 and MX Tri-Flute tools; it would be beneficial to assess the response of these models in a different material and with different tools. For instance, it would be very interesting, if datasets are available, to evaluate the behaviour of the presented studies in more challenging materials such as steels or titanium alloys.

The studies presented in this thesis can be extended to the analysis of different manufacturing processes. Nowadays, several companies are producing and storing data of their processes but the information is not used at its full potential (extracting value from Big Data). The systems engineering frameworks and models presented in this research investigation are generic could be applicable to other processes.

In terms of the 'Novelty Detection' framework and spectral analysis, their applications could be extended to identify the different types of flaw or defects that can affect the quality of the process. Some of the defects are difficult to detect even with destructive testing techniques. An application which can indicate the type of defect would be extremely helpful for industries.

Finally, in terms of HCS, it was demonstrated how one can take advantage of traits of FL systems and develop human-friendly computational systems. Further such opportunities can be explored in the field of Systems Engineering, in particular in the area of natural language processing and Cognitive Computing. A fully autonomous system which integrates the prediction, novelty detection, multi-objective optimisation and natural communication with the user would be an interesting application to demonstrate how the system can work within a loop based on the feedback provided from the models.

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9 Appendices

Appendix 1

Table 9.1 Summary of weld data for individual probe features

Tool component	Spindle torque, Nm	Down force kN	Maximum tool temperature C	Traverse force kN	Average maximum bending force, kN
Plain cone	102.7	39.6	466	6.3	6
Threaded cone	105.7	45.7	503	4.3	5.5
Triflute™	104.3	38.4	507	3.9	4
Triflat™	103.0	39.2	485	4.2	4.5
MX-Triflute™	104.0	45.3	511	3.1	3.5
MX-Triflat™	107.8	46.8	510	3.2	3.75

(Beamish and Russell, 2010a)

Table 9.2 Summary of weld microstructural features for individual probe designs

Tool component	Material movement	Weld surface	Weld root	Joint line remnant present
Plain cone	Some material movement.	Shoulder dominates material movement. Deep layer of scalloped bands.	Linear feature created by discontinuity in material flow.	Yes
Threaded cone	Improved material movement.	Tool probe features effect material movement. Reduced layer of scalloped bands.	Material heavily worked however flow discontinuity remains. Characteristic bulge added to advancing side of weld root.	No
Triflute™	Significantly improved flow and weld formation.	Material aggressively worked by probe. Very shallow shoulder scallops.	Good weld formation, flow discontinuity removed. Inward facing striations in root.	Yes
Triflat™	Significantly improve flow and weld formation.	Gradual transition from shoulder to probe induced material movement.	Good weld formation, flow discontinuity removed. Outward facing striations in root	Yes
MX-Triflute™	Good material flow and weld formation.	Material aggressively worked by probe. Very shallow shoulder scallops.	Good weld formation, flow discontinuity removed. Inward facing striations in root.	No
MX-Triflat™	Good material flow and weld formation.	Gradual transition from shoulder to probe induced material movement.	Good weld formation, flow discontinuity removed. Irregular striation pattern.	No

(Beamish and Russell, 2010a)

Appendix 1

Table 9.3 Summary of online and offline inspection techniques for FSW

Monitoring / inspection type	Application	Advantages	Disadvantages
Online monitoring (e.g., process parameters, temperature, weld path errors)	Correlation to flaws detected during process development and qualification	Simple and quickly identifies problems while a part is being made	Requires well-defined process window that accurately determines range of process parameters
Visual monitoring	Flash, galling, lack of shoulder or pin penetration, cracking, misalignment, distortion	Quickly identifies problems while a part is being made Minimal surface preparation Reduced need for other (Nondestructive examination) NDE methods	Only able to detect visible surfaces flaws Observations vary with personnel experience Surface cleaning and preparation Distractions Poor resolution Eye fatigue Good illumination required
Analytical sensing	Detection of flaws correlated to signal analysis study	Capable of predicting weld flaws while part is being made Reduced need for other NDE methods	In early phase of research and much work still needs to be performed
Offline monitoring of data	Correlation to flaws detected during process development and qualification	Simple and quickly identifies problems	Requires well defined process window that accurately determines range of process parameters
Radiography	Inclusions, cracks, porosity, corrosion, debris, lack of fusion, lack of penetration, leak paths	Sensitive to finding discontinuities throughout the volume of materials Easily understood permanent record Full volumetric examination Portability	Radiation hazard, relatively expensive, long set-up time, necessary access to both sides of specimen Depth of indication not shown High degree of skill required for technique and interpretation Lack of sensivity to fine cracks
Dye penetrant	Cracks, porosity, leak paths, seams, laps	Inexpensive, sensitive, minimal equipment, application to irregular shapes, versatile, minimal training	Non-porous surfaces only Detection of surface flaws only Messy Ventilation requirements
Ultrasonic	Detect lack of penetration Detect wormholes Discontinuities in surface and subsurface Thickness measurements	Fast Only single-sided access is required Full volumetric information Minimal part preparation is required Instantaneous results Detailed images can be produced automatically Permanent record Can be used for thickness measurements	Surface must be accessible and smooth Can have operator dependence Flaw orientation important: linear defects oriented parallel to the sound beam may go undetected Interpretation can be difficult Need for reference standards Difficulty with complex geometries Inability to pads through air – need for couplant.
Phased array eddy current	Cracks, inclusions, dents, and holes Detect lack of penetration Detects galling Coating and material thickness Surface and near surface defects Composition / conductivity / permeability Grain size / hardness Dimensions and geometry Alloy sorting	Fast Inspection done in one pass Allow bead width sizing (indirect detection of oxide layers) Full coverage of weld c-scan imagining for easy interpretation easy to operate automation available permanent record available specimen contact not necessary	Manual surface testing is slow Interpretation may be difficult Depth of penetration is limited Flaw orientation is critical Specimen must be electrically conductive Sensitive to many specimen parameters Surface roughness can produce non – relevant indications.

(Zappia, 2010)

Appendix 2

Table 9.4 Training and testing data for elongation

	Tool rotational speed (RPM)	Traverse speed (mm/min)	Elongation (%)
TRAINING DATA	280	168	19.9029
	280	224	21.4184
	280	336	20.7682
	280	392	18.6968
	355	213	21.1851
	355	284	18.5264
	355	426	21.5080
	355	497	20.0090
	430	258	21.3005
	430	344	25.3713
	430	516	19.6417
	430	602	19.1110
	505	303	18.8152
	505	404	19.6443
	505	606	21.1323
	505	707	20.7148
	580	348	20.0604
	580	464	12.1529
	580	696	10.7151
	580	812	09.8258
TESTING DATA	280	280	20.1078
	355	355	21.7179
	430	430	17.9744
	505	505	13.4041
	580	580	14.9365

Appendix 2

Table 9.5 Training and testing data for ROA

	Tool rotational speed (RPM)	Traverse speed (mm/min)	Reduction Of Area (%)
TRAINING DATA	280	168	33.9460
	280	224	31.8447
	280	336	30.9170
	280	392	29.8833
	355	213	28.2068
	355	284	28.4004
	355	426	30.7075
	355	497	29.3227
	505	303	27.2983
	505	404	27.2994
	505	505	20.3864
	505	707	30.9903
	580	464	13.6552
	580	580	18.0198
	580	696	15.1141
	580	812	13.0070
TESTING DATA	280	280	32.9301
	355	355	32.6291
	505	606	33.3349
	580	348	30.3553

Appendix 2

Table 9.6 Training and testing data for UTS

	Tool rotational speed (RPM)	Traverse speed (mm/min)	UTS (MPa)
TRAINING DATA	280	168	314.7806
	280	224	314.0579
	280	336	314.2965
	280	392	314.9759
	355	213	313.5182
	355	284	310.5434
	355	426	312.5699
	355	497	310.6121
	430	344	295.9089
	430	430	266.3400
	430	516	281.3056
	430	602	296.1344
	505	303	315.2544
	505	404	305.9747
	505	505	275.7257
	505	707	315.9479
	580	464	229.0648
	580	580	292.1812
	580	696	263.5498
	580	812	258.1556
TESTING DATA	280	280	314.5284
	355	355	312.6803
	430	258	300.2489
	505	606	320.1107
	580	348	315.2621

Appendix 2

Table 9.7 Training and testing data for yield strength

	Tool rotational speed (RPM)	Traverse speed (mm/min)	Yield strength (%)
TRAINING DATA	280	168	171.8666
	280	224	173.0938
	280	336	176.6526
	280	392	184.0504
	355	213	171.4650
	355	284	172.5717
	355	426	174.7096
	355	497	173.4202
	430	258	163.3000
	430	344	169.9000
	430	516	163.6000
	430	602	169.0000
	505	303	173.8484
	505	404	173.5826
	505	606	177.3667
	505	707	177.8281
	580	348	173.6538
	580	464	175.7041
	580	696	177.7214
	580	812	176.5837
TESTING DATA	280	280	173.0029
	355	355	173.9246
	430	430	162.8000
	505	505	174.9407
	580	580	175.8759

Appendix 2

Table 9.8 Training and testing data for average grain size

	Tool rotational speed (RPM)	Traverse speed (mm/min)	Average grain size (μm)
TRAINING DATA	280	168	11.9639
	280	336	8.6111
	280	392	6.9829
	355	213	11.7667
	355	284	11.9665
	355	426	9.7164
	430	516	10.7752
	505	303	12.8799
	505	707	11.2733
	580	812	9.3194
TESTING DATA	280	280	8.8966
	355	355	10.7214
	430	258	14.5185
	505	606	13.0866
	580	348	12.2854

Table 9.9 Training and testing data for cooling rate

	Tool rotational speed (RPM)	Traverse speed (mm/min)	Cooling Rate (°C/s)
TRAINING DATA	300	300	13.1
	300	420	30.7
	300	480	35.2
	400	400	13.8
	400	560	63.3
	400	640	66.5
	500	600	87.9
	500	700	103.5
	500	800	84.2
	600	720	91.6
	600	840	93.9
	600	960	130
	700	800	129.8
TESTING DATA	300	360	23.3
	400	480	18.9
	500	500	20.5
	600	600	40.8
	700	700	71.1

Appendix 2

Table 9.10 Training and testing data for weld quality

	Tool rotational speed (RPM)	Traverse speed (mm/min)	Weld quality (0-12)
TRAINING DATA	280	168	0
	280	224	0
	280	336	0
	280	392	2
	355	213	1
	355	284	0
	355	426	0
	355	497	1
	430	258	0
	430	344	0
	430	516	1
	430	602	1
	505	303	0
	505	404	0
	505	606	0
	505	707	2
	580	348	2
	580	464	2
	580	696	5
	580	812	8
TESTING DATA	280	280	0
	355	355	0
	430	430	0
	505	505	1
	580	580	1